Discretionary Credit Rating and Bank Stability During a Financial Crisis

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Abstract

In this paper we study the incentives for discretionary credit risk assessment under current banking regulation. By studying the capacity of firms' credit ratings in predicting default for the case of Slovenian banking system during the Great recession this paper shows that banks in financial distress tend to underestimate credit risk. Our results show that predictive accuracy of ratings deteriorated in the crisis both in absolute terms and relative to the benchmark logit model. Moreover, we show that predictive accuracy was lowest for domestically owned banks and, within this group, for small banks. We argue that these banks also had the largest incentives to under-value risk because their portfolios were more exposed to non-performing loans and had limited possibilities to raise additional capital. Given that credit ratings are closely related to the rates of loan-loss provisions, our analysis indicates that under-estimation of credit risk served to inflate banks' books. These findings can also rationalize the results of the comprehensive review of the Slovenian banking system in 2013, which revealed significant differences in required recapitalizations across groups of banks that had differing incentives to under-estimate risk. A number of robustness checks confirm the validity of our conclusions. Our findings provide a plausible explanation of potential similar findings at the conclusion of the comprehensive review in the Euro area prior to the launch of the Single Supervisory Mechanism.

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[1]The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of Bank of Slovenia.

1. Introduction

Existing accounting standards and banking regulation through capital adequacy requirements induce procyclicality in the loan-loss provisions.[2] In economic downturns the incidence of loan 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 apply discretion and relax standards of credit risk assessment and valuation of assets in times of economic downturn. Such 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. In a financial crisis raising wholesale funding or additional capital to meet with minimum capital requirements is particularly difficult, which only increases the incentives for discretion in credit risk assessment. 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).

Discretion in banks' valuation of assets is analysed, for example, 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. 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 capitalized banks, who have higher incentive to under-report actual riskiness. 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.

This paper focuses on discretion in credit risk assessment. We study the case of Slovenia in the financial crisis that began in 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 approved by the European Central Bank. The results, announced publicly in December 2013, revealed significant shortages of capital even though prior to the comprehensive review all banks under examination reported sufficient regulatory capital adequacy ratios (see Full report on the comprehensive review of the banking system, Bank of Slovenia, 2013). In particular, required recapitalization for all banks under examination amounted to 214% of existing capital, indicating 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.[3] These results were to a large extent conditioned by a strict methodology for valuation of collateral used in the AQR process. However, there are cross-sectional differences among banks that cannot be attributed to valuation methodology.

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

[3]These two banks were subsequently excluded from the stress test part of the comprehensive review.

Namely, there were stark differences in the required recapitalization between domestic and foreign owned banks. For the former the additional capital required 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. 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%.

The above grouping of banks according to ownership structure (domestic - foreign, private - state) and size corresponds to different factors that underlie the incentives to apply discretion in risk assessment. An important factor is the ability to raise capital in times of financial distress. Large domestic banks, even dominantly state owned as was the case of two largest Slovenian banks, enjoy the implicit bail-out guarantee by the government. Smaller banks with financially weak owners face difficulties in raising capital and thus have stronger incentives to apply discretion in risk assessment in face of mounting distress in their assets. Foreign owned banks have access to the internal capital markets of international banking groups they belong to and thus have access to more stable sources of funding (Navaretti et al., 2010; de Haas and Lelyveld, 2010).

All of the banks included in the Slovenian comprehensive review operated in the same market and were exposed to same systematic risks and the same regulatory environment. The differences in required recapitalizations can be in principle attributed to different factors of which we focus on discretion in credit risk assessment. 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 below, 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, however, important heterogeneity in these results across groups of banks. In line with the above mentioned differences in the required recapitalisation after 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.

The results on predictive capacity of credit ratings align with the results of required amounts of recapitalization. Although operating in the same regulatory environment, banks with bigger exposures to credit risk had more pronounced incentives to apply laxer standards in credit risk assessment. In turn, their credit ratings result to be worse in predicting financial distress of their clients.

These results bear important implications for regulatory policy and problems due to regulatory forbearance. The 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. Non-performing loan ratios were considerably higher in domestically owned banks. Such differences point to differences in incentives for fair risk assessment and signal to the regulator potential excessive concentration of risk that might eventually result in such dramatic problems with solvency as revealed by the comprehensive review in Slovenia. Our analysis indicates that a robust regulatory policy needs to take into account developments in the financial system that increase incentives for discretionary over-optimistic risk assessment and valuation of assets and react in a forward-looking and pre-emptive manner. This will simultaneously reduce also the necessity to resort to regulatory forbearance.

The rest of the paper is organized as follows. Section 2 describes banks' incentives for discretionary risk assessment. Section 3 presents our modelling approach for testing predictive power of credit ratings and discretion in credit risk assessment. Section 4 presents the main results. Section 5 contains three sets of robustness checks, while Section 6 concludes and discusses policy implications.

2. Incentives for discretionary risk assessment

In this section we provide the empirical evidence of 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, where we divide banks according to size and ownership.

The source of credit ratings data is the Credit Registry data of the Bank of Slovenia. The Credit Registry is a rich database with many bank-borrower information that are not publicly available. Among others, it contains data on credit ratings banks assign to their clients. 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 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). 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. Banks classify borrowers into credit grades based on the assessment of their financial position, the ability to provide sufficient cash flow to regularly fulfill the obligations to the bank, and information on the borrowers' potential arrears in loan repayments. The latter is regularly available to the banks and in practice carries significant role in determining the credit rating.

We combine the data from the Credit Registry 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. The banks are mandatory to report the data to the Credit register every month, but since firms' balance sheet and income statement data are only available at yearly basis, we use the end-of-year data from 2006 to 2012. In the analysis we include only non-financial corporations.

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 from 2006 to 2012. On the other hand, the share of the worst performing borrowers rated D or E increased by 6.8 percentage points in both rating classes respectively. 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. This shows 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
Weighted by the number 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
Weighted by banks' exposure to borrowers							
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 into their balance sheets. In principle, for each individual firm loan-loss provisions need not increase automatically in response to a worse credit rating of 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 grades A, B and C the banks calculate the incurred loss for the borrowers that migrated to grades D or E and thus determine their internally required coverage ratio for each of these three rating classes. The banks are required to regularly update the migration matrices, meaning that their required coverage ratio is changing in time. Collateral also plays an important role in provisioning. Banks can apply lower coverage ratio for the borrowers that pledged 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 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 determine 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. However, for smaller loans banks can also assess provisions collectively even if they are non-performing.

Table 2 reports the average coverage of outstanding corporate loans with loan-loss provisions (end-of-period stocks) banks held across credit rating classes in the period 2006-2012. It is evident that on average banks need to provide more for expected loan losses for firms with lower credit ratings. Even though the exact rate of loan-loss provisions depends also on 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 significant deterioration and a significant 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.

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 of 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. 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 should be the result of banks' specificities in credit risk assessment and should not be conditioned by firm characteristics. Table 3 shows that banks apply on average different rates of loan-loss provisions across credit rating categories assigned to the same firms. For instance, the difference in applied 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 principle, in addition to having the incentive to overestimate credit ratings banks have an incentive to overvalue collateral (see Huizinga and Laeven, 2012). In particular, banks with weak position in collateral would have 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 mean that the true differences between credit-rating classes would only be larger than reported in Tables 2 and 3.

Overall, the results in Table 3 are in line with those in Table 2. They confirm 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 is provided by Volk (2012). He notices that even though the banks downgraded a considerable share of borrowers, their assessment of firms' riskiness changed significantly during the financial crisis. By using a conventional probit model of probability of default the imputed probabilities of default exhibit an increase in credit grades A, B and C. This indicates that the risk assessment strategy by the banks might have significantly changed over time.

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 banks into three groups. The first division is according to residence of owners: foreign vs domestic. Foreign-owned banks are part of multinational banking groups who have easier access to wholesale finance and can provide funds to daughter affiliates through the internal capital market. Our prior therefore is that foreign-owned banks have better capacity to absorb credit losses and consequently their management less incentives to apply discretion in credit risk assessment.

The second division is that of domestic banks into large and small. The group of large domestic banks consists of three banks. Two, NLB and NKBM bank, are the largest two on the market, holding more than 35% of total bank assets. From the point of view of the ability 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. 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 included not merely because of its size, but because it is a 100% state-owned bank. This

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.

The division of banks into subgroups, especially with respect to ownership to foreign and domestically owned, is interesting from the point of view of the comprehensive review conducted in 10 Slovenian banks in the second half of 2013.[4] Results of the AQR, made available to the general public in December 2013, revealed significant shortages of bank capital that differed significantly across the three groups of banks. For the domestically owned banks the additional capital required amounted to 244% of existing capital (as reported at the end of 2012), while for the foreign-owned banks this figure was "only" 78%. Also within the group of domestic banks we can find important differences. The capital shortfall for the largest two banks on the market was estimated at 228% of existing capital, while for the small and predominantly privately owned the figure was 274%.

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. By international standards these levels of shares of NPLs in total corporate loans outstanding are very high. The increasing dynamics in foreign-owned banks was significantly less pronounced, which combined with the fact that the comprehensive review revealed a much smaller required recapitalization for foreign banks leads to a conclusion that prior to the crisis foreign-owned banks led a more prudent lending policy.[5] Similarly, we can conclude 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%). This 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 quite significantly and thus did not let the required provisions on expected losses from the NPLs to pass on to their profit and loss accounts.

To outline further the differences across bank groups in response to financial distress we look at the changes in credit ratings through time. Figure 1 reports the share of rating changes per year in the period 2007 - 2012 divided into rating cuts (left panel) and ratings upgrades (right panel). Overall, it clearly emerges from the figure that as the crisis evolved the frequency of rating cuts increased. From roughly 10% ratings that changed on average in 2007 their share increased

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[4]Two domestically owned banks were subsequently excluded from the stress test part of the exercise as a result of the initiated insolvency procedure by the central bank. Nevertheless, the required recapitalisation was calculated also for these two banks.

[5]A higher degree of prudence is mostly in the sense of better selection of borrowers and not in terms of a smaller rate of expansion of lending activity as foreign-owned banks 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.

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.

to above 20% on average in 2012. The share of rating upgrades on average hovered around 5% rate 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 cuts 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 rating cuts to 30%, while in domestic banks it leveled off at 20%. It is true that foreign-owned banks led also the pace of rating upgrades, while domestic bank lowered this rates to levels below 5%, however, the rates of rating upgrades did not exceed one third of the rates of rating cuts. This implies that on net foreign banks led the 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.

Similar to the findings above, 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. Domestically owned and smaller banks with the smallest capacity to absorb losses had the highest incentives to conceal the true creditworthiness of their clients. This is reflected in the relative dynamics of rating changes during the Great recession.

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

Our approach to testing the potential bias in credit risk assessment in times of economic downturn is the following. We focus on the banks' loans to non-financial corporations as this segment of bank portfolios held the dominant share of non-performing loans in the period 2007 - 2012. Namely, 80% of overall value of loans more than 90 days overdue (our measure of default) were within the segment of loans to non-financial corporations. For these corporations we have access to data on their credit rating as assigned by corresponding banks. In the process of credit risk assessment banks dispose with information on firms' balance sheet and income statement, which is also publicly available, 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 by an econometrician in modeling 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

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

(a) Rating cuts

(b) Rating upgrades
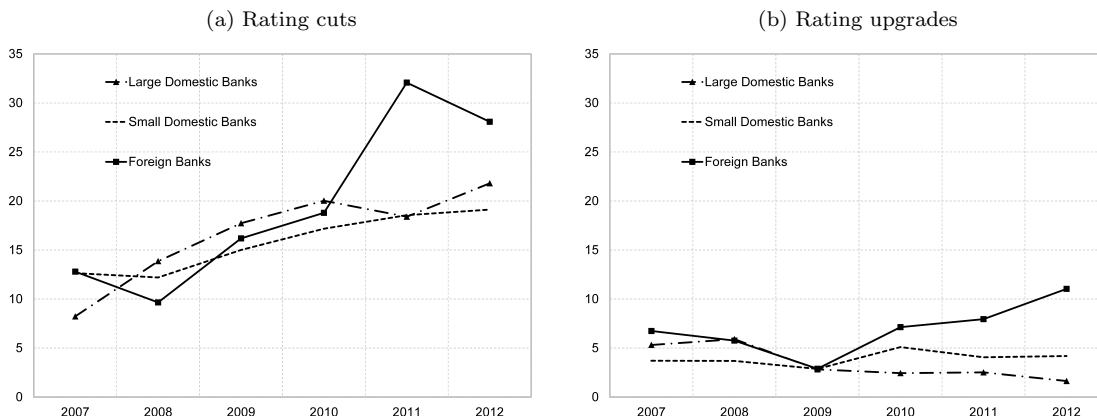
Source: Bank of Slovenia, authors' calculations.

about firms' creditworthiness relative to the information contained in standard financial ratios. 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 sets of information, one in the form of pure financial ratios and the other in the form of credit ratings. We take both sets of information and include them separately in two econometric models. The model using pure financial information is denoted below as the *balance-sheet model*. The model that use the information embedded in credit ratings is denoted as the *credit-ratings model*. Both models have a common parametric structure: logistic regression. With both we test for respective classifications accuracy of defaulted firms. Given common parametric assumptions, the differences in explanatory power of default between the two models are due to differences in the information used by the two models.

Based on this we can test two hypotheses. First, as discussed above, credit ratings should embed superior information and expert knowledge in assessing creditworthiness. In this respect we can first test whether credit ratings are a more precise determinant of corporate default. Second and more importantly, such a setting allows us to test for the presence of underestimation of credit risk in response to a deteriorating capital adequacy in the period of a crisis. If in times of economic distress banks have more incentives to apply discretion in credit risk assessment so as to underestimate risk we should observe a reduction in explanatory power of credit ratings for probability of default. 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, 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 the 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, two 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 ratios. Because the latter in principle enter the information set of both models then the models should be equally affected by a potential reduction in explanatory power of financial ratios.

Secondly, with exception of one, all of the banks in our sample conducted a standardized approach to determining capital requirements for credit risk. Our testing approach would be applicable also for banks using the internal based rating (IRB) system. Under IRB banks use a fully parametric model to determine one of the key ingredients to calculating capital requirements: probability of default. [6] 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. 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.

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 in the literature largely used as indicator of default (Bonfim, 2009, Carling et al., 2007, and others). Such indicator is also in line with the Basel (BCBS, 2006) recommendations. We define the event of default as follows:

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

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

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[6]The 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 modelling probability of default.

estimated using the following model specification:

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

where α and β are parameters to be estimated and X_{it-1} is a vector of firm specific variables including measures of firm size, age, liquidity, indebtedness, cash flow and efficiency. In addition to balance sheet and income statement variables, we follow Volk (2012) and include the number of days a firm has blocked bank account and number of bank-borrower relationships, which were both found as important risk drivers. Moreover, this information is also available to banks in the process of assessing firms' creditworthiness. All explanatory variables enter the model lagged one period.

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 estimate the 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

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

and estimate the logit model:

$$P(Y_{ijt} = 1|R_{ijt-1}) = \Lambda(\alpha + \beta R_{ijt-1}) = \frac{e^{\alpha+\beta R_{ijt-1}}}{1 + e^{\alpha+\beta R_{ijt-1}}} \tag{4}$$

where α and β are parameters to be estimated and R_{ijt-1} is a set of five 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 presents the estimated coefficients of the balance sheet and credit ratings model respectively. The explanatory variables in the balance-sheet model follow Volk (2012). 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). These variables are consistently statistically significant explanatory variables of financial distress in the period under analysis.

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

12

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***
No. of days with bl. ac._{it-1}	0.011***	0.011***	0.012***	0.012***	0.014***	0.014***
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.

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 marginally less so for the balance sheet model), the classification accuracy of defaulted firm exhibits more pronounced dynamics that is depicted in Figure 2. What we observe is that before the crisis (default in 2007 based on 2006 data) both models had a very similar default 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.[7] 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 perfectly healthy. What is surprising is the fact that the deterioration in classification precision is higher for the credit ratings model. The 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 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 in the economy. 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 the bank balance sheets.

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%. Overall, this comparison provides time-series evidence of a potential problem with 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.

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.

[7]Slovenia slid into a recession in the fourth quarter of 2008.

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.

Figure 2: Correctly Classified Defaulters (in %)
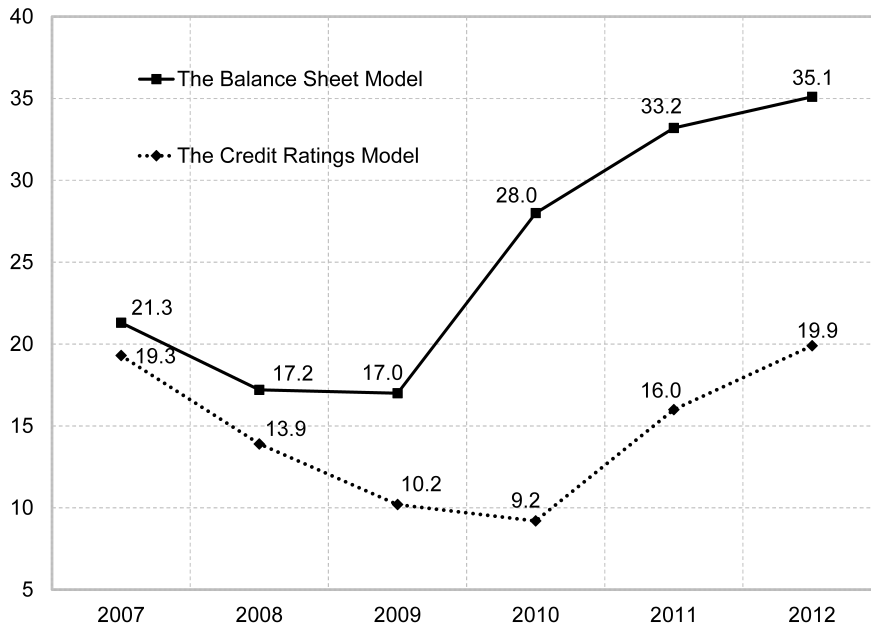
Source: Bank of Slovenia, AJPES, author' calculations.

15

What we can observe is 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 two years under analysis. The experience of the classification accuracy of credit ratings of small banks is at the opposite end of the spectrum. While they perform 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 stands in between. While being the least precise before the crisis and the initial two years, it actually picks up quite significantly at the end of the period, reaching levels of precision above 20%, which is double the pre-crisis rate.

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, both because of a stronger initial capital adequacy and more stable access to finance through internal capital market of the banking groups they belong to. 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 problem 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 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 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.

5. Robustness checks

In this section we consider three sets of 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. We did not, however, control for the timing of updating the information set. This raises several issues that might plague our previous analysis.

First, 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.

Figure 3: Correctly Classified Defaulters Across Groups of Banks (in %)
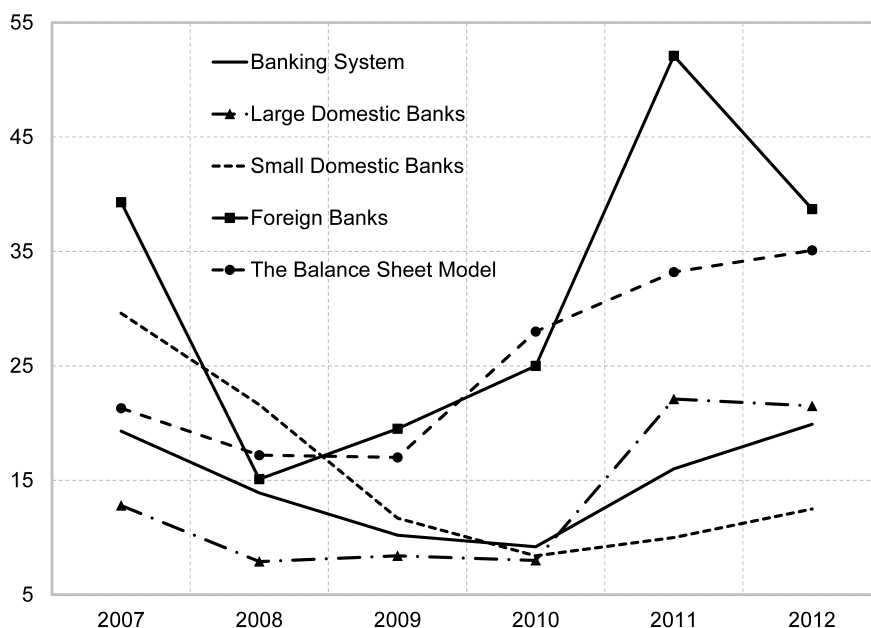
Source: Bank of Slovenia, AJPES, authors' calculations.

Second, forecast horizon in default prediction might play a role in banks' decision making. This is especially so in the period of financial crises where prompt reaction is required in face of mounting bad loan burden.

Third, corporate balance sheet and income statement data are published once a year and with delays. In Slovenia, firms are required to report by the end of March of current year for the past fiscal year. This means that it is also end of the first quarter of the current year that they can report to banks about their financial status as per end of past year. The balance sheet model estimates in the previous sections, however, assumes that this information is available at the end of each year. 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 and these contain the information sets banks have in real time.

5.1. Controlling for rating changes

Data on credit ratings is on quarterly and even on monthly frequency after 2009, which enables us to trace the timing of rating changes and hence the time when a bank updated the information set. This approach leads to some imperfections since we cannot identify cases where information set was updated but rating did not change. Nevertheless, controlling for rating changes could improve the performance of the credit rating model. We thus estimated the credit rating model in which we control for the rating change and compare its classification accuracy with the model without the control rating change.

Classification accuracy of credit rating models with and without dummy variable for rating change is shown in Figure 4. For the whole banking system, rating change improves the share of correctly classified defaulters in 14 out of 21 quarters, for which the model is estimated. In the cases where its impact is positive, it contributes on average 4.8 percentage points to the

17

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 behavior 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.

Figure 4: Correctly Classified Defaulters Four Quarters Ahead Across Groups of Banks (in %)
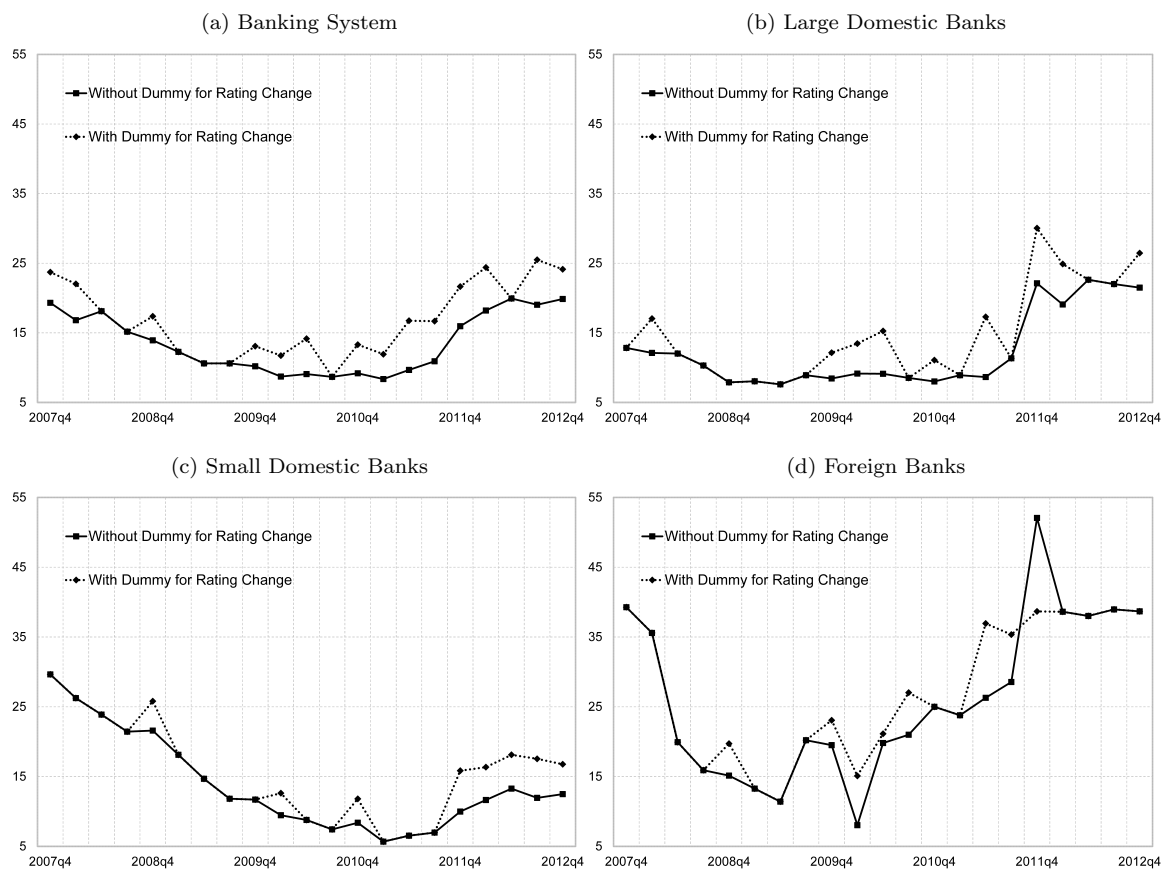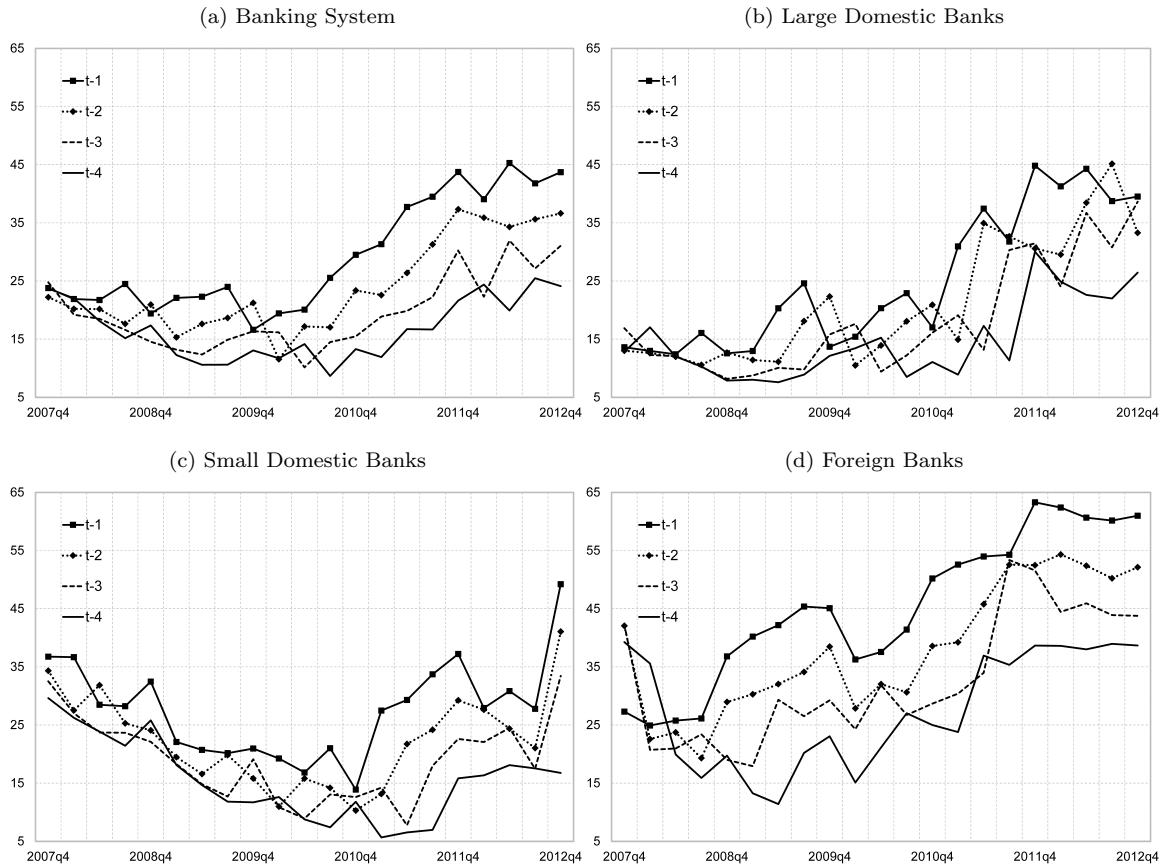

Source: Bank of Slovenia, authors' calculations.

5.2. Controlling for forecast horizon

Thus far we considered predicting default 1 year ahead. However, managing risk in a financial crisis requires prompt reaction, thus we check robustness also at shorter horizons. For this purpose, we estimate the credit rating model for each quarter from 2007q4 to 2012q4, with different lags of explanatory variables, from 1 to 4 quarters. We also control for the rating change in the model. The percentages of correctly classified defaulters across groups of banks are

depicted in Figure 5. As expected, the shorter the information lag, the better the performance. From the point of view of our analysis, however, it is important to observe that the relative comparison of classification accuracy between groups of banks that we identified in the previous section stay robust also on shorter horizons.

Figure 5: Correctly Classified Defaulters Across Groups of Banks and Different Information Lags (in %)

(a) Banking System

(b) Large Domestic Banks

(c) Small Domestic Banks

(d) Foreign Banks

Source: Bank of Slovenia, authors' calculations.

5.3. Controlling for public release of corporate balance sheet data

Firms are required to report their balance sheet data for the previous year until the end of March of current year, but the data typically become available during the second quarter. We could thus assume that banks are newly informed about the financial state of each firm in the second quarter of each year. This holds especially for smaller firms, whereas larger firms, to which bank has larger exposures, are monitored regularly. In addition, an important information, which is regularly available to the banks for all firms is their repayment history. Possible delays in loan repayment clearly indicates that a firm has financial problems. Such an information is an important determinant of the credit rating.

In order to check whether the timing of public release of balance sheet and income statement has an effect on the dynamics of rating changes, we first check simple descriptive statistics.

19

We again use the data about rating changes and calculate the percentage of changes over the quarters. Table 8 shows that rating changes are approximately equally distributed over the year. If the newly available balance sheet data would be the main drivers of rating changes, we could expect that the large majority of changes would happen in the second and third quarter. Results in the table indicate that this is not systematically the case. This indicates that banks rely also on other more up-to-date sources of information about firms' financial state, which allows to adjust firms' ratings accordingly throughout the year.

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.
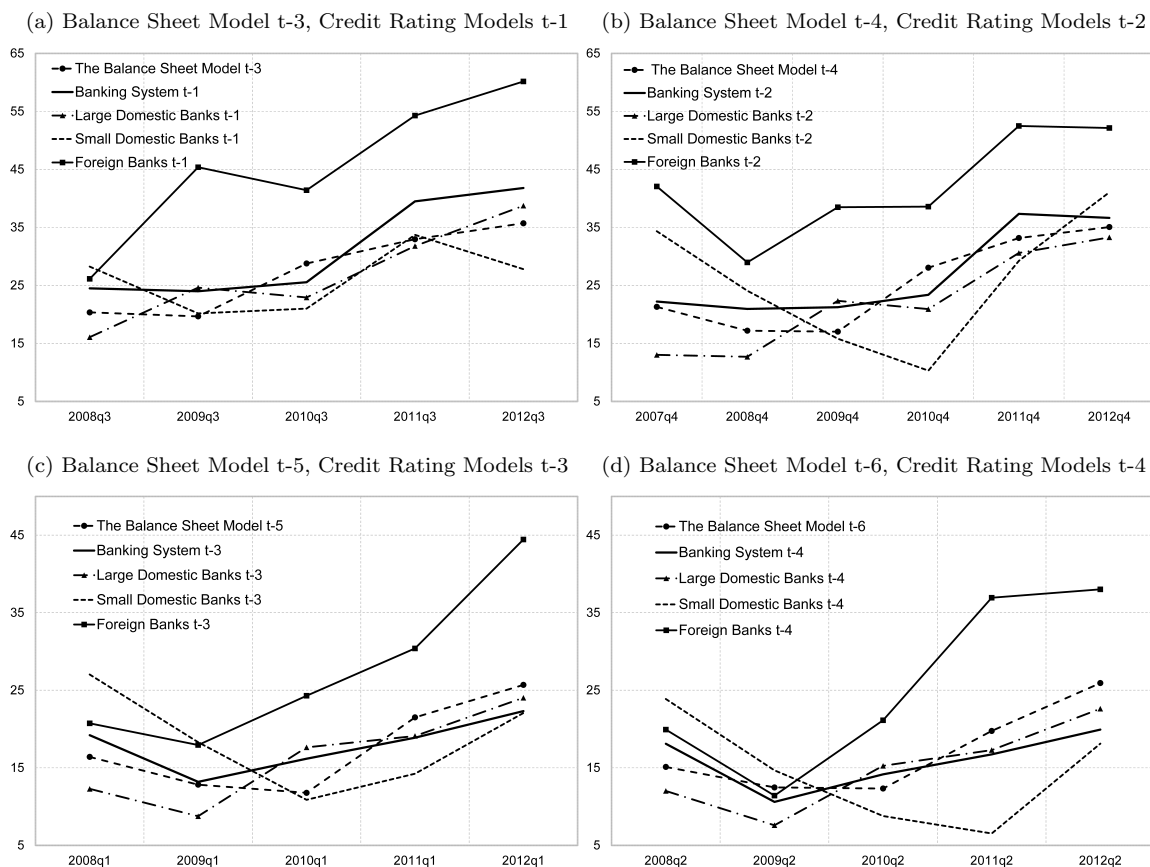
A priori the timing of release of public information does not seem to be a decisive element in determining the relative performance of the credit ratings model. Nevertheless, we explore a possible information advantage of the balance sheet model by comparing its classification performance with the credit rating model for the period when the same set of information as used in the balance sheet model is also available to the banks. Similar as in previous two subsections, the credit rating model is augmented with the dummy variable for rating change. Since balance sheet data for previous year are available to the banks in the second quarter of current year it is senseless to compare the performance of both models for the first two quarters. We thus compare the performance in Q3 and Q4 with the balance sheet data from the previous year (3. and 4. lag in the balance sheet model, respectively) and credit ratings from Q2 (1. and 2. lag in the credit rating model, respectively), when the same balance sheet data are also available to the banks. Due to the short lags, this gives a certain information advantage to the credit rating model, especially for financially weak firms which become overdue with loan repayment. Hence, we also make a similar comparison on longer lags, i.e. 5. and 6. lag in the balance sheet model in comparison to 3. and 4. lag in credit rating model, respectively.

Figure 6 shows the classification accuracy of the balance sheet model and the credit rating model, where the same set of balance sheet data is used in both models. Although the performance of the credit rating models is now improved in relation to the balance sheet model, our conclusions are still very robust. Similar as before, the credit ratings model estimated for the group of foreign banks outperforms all the other models, especially in the crisis period. On the other hand, the classification accuracy of small domestic banks dropped considerably during the crisis, which is the most pronounced in sub-figure (d). It declined both relative to other banking groups and, more importantly, to the balance sheet model. This is another indication that our basic conclusions 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

Figure 6: Correctly Classified Defaulters Across Different Information Lags (in %)

(a) Balance Sheet Model t-3, Credit Rating Models t-1

(b) Balance Sheet Model t-4, Credit Rating Models t-2

(c) Balance Sheet Model t-5, Credit Rating Models t-3

(d) Balance Sheet Model t-6, Credit Rating Models t-4

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

21

the system in the second half of 2013 went through a comprehensive review similar to comprehensive reviews major banks in the Euro area need to go 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), but also with respect to ease of access to the capital market and wholesale funding. 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 a unique data set containing information 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 results, provided to be the least reliable indicators of the incidence of financial distress of borrowers. These conclusions remain valid also after consider three sets of robustness checks about the information structure in the credit rating process.

These empirical findings have several 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 revealed eventually, credit risk realized and losses incurred. These losses are higher the longer under-estimation of risk postpones solving the problems. As it turned out for the case of Slovenia, two of the banks included in the comprehensive review started insolvency procedures already before the review was completed, while the rest of the domestic banks were either already nationalised or are facing nationalisation. The estimated direct fiscal costs of bailing out these banks exceeded 10% of GDP.

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 has been 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 in the primary domain of banks and thus 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.

Last but not least, 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 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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