Loss given default determinants in a commercial bank lending: an emerging market case study[*]

Marko Košak[1], Jure Poljšak[2]

Abstract

The purpose of this paper is to analyse the loss given default (LGD) determinants in case of a typical loan portfolio consisting of SME loans in a commercial bank operating in one of the quickly developing banking markets, i.e. in Slovenia. Accurate LGD estimates of defaulted bank claims are important for provisioning reserves for credit losses, calculating adequate risk capital and determining fair pricing risky bank loans. While most of the empirical literature in the field concentrates on corporate bond markets to estimate losses in the event of default, we use a unique individual bank data set on SME loan losses. Due to the proprietary nature of data only few studies of this kind have been published so far and to our knowledge none of them covers the Eastern European banking markets. In the first stage of the analysis we estimate the LGD variable by applying the discounted cash flow approach, while in the second stage we analyse its determinants by using the ordinal regression analysis. Our findings suggest that reliable LGD estimates can be produced by discounting expected loan related future cash flows and that explanatory factors, such as type of collateral, type of industrial sector, last available loan rating, size of the debt and loan maturity satisfactorily explicate variability of the LGD variable in the specific banking market. All the results are not only relevant to the impairment policy determination and capital adequacy calculation in the specific bank, but also to the evaluation of SME loans characteristics in developing markets.

Key words: bank, SME loans, loss-given-default (LGD)

JEL classification: G21, G32

[1] *Associate Professor, University of Ljubljana, Faculty of Economics, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia. Scientific affiliation: banking and finance. Phone: +386 1 5892 561. E-mail: marko.kosak@ef.uni-lj.si. Personal website: http://www.ef.uni-lj.si/pedagogi/pedagog. asp?id=147*

[2] *Corporate finance analyst. Abanka Vipa d.d., Slovenska cesta 58, 1000 Ljubljana, Slovenia, and research project participant at the University of Ljubljana, Faculty of Economics, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia. Scientific affiliation: finance. Phone: +386 1 4718 100. E-mail: jure.poljsak@abanka.si*

1. Introduction

Credit risk management has always been a central issue in successful commercial bank management and therefore deserves a lot of attention of bank managers. Despite this central position of credit risk management more sophisticated risk measurement techniques have emerged only recently and represent perhaps the principal and most challenging area of risk management. This prominence has been motivated by a number of factors in the last decade, including the development of the Basel II capital standards and implementation of Capital Adequacy Directive (CAD III) in the European Union. The new capital adequacy regulation stimulates banks to develop and use their own internal credit risk measurement models. Most of these models are based on the estimation of three crucial parameters: probability of default (PD), loss given default (LGD) and correlations across defaults (e.g. Crouhy et al., 2000; Schuermann, 2001).

Additionally, efficient credit risk management techniques have become extremely important for commercial banks operating in quickly growing emerging markets, where accelerated credit growth may significantly increase credit risk exposures in individual banks. Credit markets in Eastern European countries are an example of such developments.

So both, more stimulating capital adequacy regulation measures and credit market conditions can be considered as factors encouraging banks to assess the risks inherent in each individual credit agreement in more detail and scrutinize more closely the borrower's future ability to repay the debt. This closer scrutiny not only contributes to more successful differentiation of risky borrowers but also enables much better pricing of loans.

This paper provides a framework to analyse the loss severity rate after a default event. We concentrate on the empirical evaluation of the LGD determinants in the case of a specific commercial bank operating in Slovenian banking market, which carries most of the characteristics typical for the brisk credit markets in Central and Eastern European region. We hypothesize that the calculation of reliable LGD estimates is possible by using the discounted cash flow approach instead of the use of corporate bond markets data to estimate losses in the event of default. In order to verify our hypothesis we test the explanatory effect of the following LGD determinants: type of collateral, type of industry, last available rating, recovery method and size of the exposure. Apart from empirical testing of the recovery rates determinants the paper elaborates on the workout costs incurred by the bank in recoveries on bad and doubtful loans. Accurate LGD estimates of defaulted bank claims are important for provisioning reserves for credit losses, calculating adequate risk capital and determining fair pricing risky bank loans. In the empirical analysis we use an unique data set on loan losses related to SME (small and medium sized enterprises) loans

over the 2001 – 2005 period[3]. To our best knowledge this is the first attempt of an empirical analysis of LGD determinants in a bank operating in one of the Eastern European banking markets.

Slovenian banking market is an example of a quickly developing banking market that has experienced solid growth rates in the entire transition period since the beginning of the 1990s and it has become the first among the Eastern European markets that was fully integrated in the Euro area with the Euro adoption in January 2007. This rapid development of the market, coupled with immense institutional and regulatory changes, has stimulated individual banks to implement contemporary risk management practices as quickly as possible. An intensified penetration of foreign banks since the beginning of the new millennium has only contributed to the accelerated implementation of up-to-date methods and techniques in daily operations.

Likewise most of the Eastern European banking markets, Slovenian market has been characterised by the accelerating credit growth rates after the EU accession and a subsequent severe stagnation in credit activity following the recent financial crisis. So, for example the annual growth rate of loans in Slovenian banking sector to non-banking borrowers increased from 14% in 2002 to 24.4% in 2006 (Bank of Slovenia, 2007) and dropped to merely 1.4% according to the annualised data reported for November 2009 (Bank of Slovenia, 2009). Taking into account the fact that total asset annual growth rates have been diminished in the pre-crisis period and deteriorated from 17% in 2002 to 15.2% in 2006 (Bank of Slovenia, 2007), we can conclude that the credit risk exposures have risen substantially[4], which has been revealed to some extent after the year 2007 when the financial crisis has escalated. Changes in the quality of the portfolio can also be detected on the aggregate level by observing the segmentation of credit claims according to the Bank of Slovenia's five level classification system from A to E, where A denotes claims of the highest quality and E uncollectible claims. In 2006 the proportion of A rated claims declined, while the proportion of B rated claims increased, if compared to 2005. Total claims rated A and B were 0.8 percentage point higher in 2006 (95.9%) than in 2005 (95.1%). The gain in top rated categories went at the expense of C rated claims. The proportion of non-performing claims, rated D and E, increased from 2.4% in 2005 to 2.6% in 2006.

Accurate LGD estimates of defaulted facilities are important for provisioning reserves for credit losses, calculating risk capital and determining fair pricing for credit-risky

---

[3] Due to the proprietary natur of data needed for the analysis, a more distant time period was used for the preparation of this paper. Therefore also all the variables were kept in the original currency and they were not recalculated into euro.

[4] Most of the excessive credit growth was possible due to massive structural changes in assets of most of the banks in the market, which disinvested safe and short term Bank of Slovenia bills and replaced them by commercial loans.

obligations. The assessment of loss changes may lead to lower capital requirements in following years as far as that is supported by sound empirical evidence.

The structure of the paper is as follows. The introduction is followed by section two, which offers a brief literature review relevant for our analysis. Measurement methods, data and explanatory variables analysis are presented in section three. The empirical model settings are presented in section four, whereas section five brings the results and section six concluding remarks.

2. Literature review

Most of the published research deals with recoveries of bonds rather than bank loans, due to the proprietary nature of data for the latter. But data unavailability is not the only difference between bank loans and bonds. The list of relevant differences contains at least the following peculiarities (Schuermann, 2001; Amihud, Garbade and Kahan, 2000):

– Bank loans are typically more senior in the capital structure of the borrowers, which can clearly affect their recovery rates.

– Banks usually more actively monitor the evolving financial health of the obligor.

– Banks as private lenders better control the agency costs of the borrowers through tighter covenants, better renegotiation possibilities and closer monitoring. All these characteristics are pretty much tight to the notion of relationship banking.

These differences are also a reason for somewhat different methodological approaches in estimating recovery rates. Nevertheless the fundamental characteristics of publicly traded debt, that can be associated with debt recovery rates turn out to be basically the same as the features of the privately placed bank loans and related recovery rates. So the studies on corporate bonds report that recovery on individual bonds is affected not only by seniority and security, but also by the industry conditions at the time of default (Dermine and Carvalho, 2006).

Altman et al. (2004) present a detailed review of the way credit risk models, developed during the last three decades, treat the recovery rate and its relationship with the probability of default of an obligor. Altman et al. (2004) also summarize and thoroughly discuss the empirical evidence on recovery rate calculation and RR – PD relationship. In the rest of this section we briefly summarize published research on RR (LGD) measurement in case of defaulted bank loans, since our study focuses strictly on individual bank loan transactions.

One of the widely quoted studies on LGD measurement of bank loans is the Asarnow and Edwards (1995) study. Asarnow and Edwards (1995) calculated loss in the event

of default (LIED) for 831 defaulted C&I loans and 89 defaulted structured loans for the 24-year period (1970-1993) in Citibank. They measured 34.79% LGD for the C&I loans and 12.75% LGD for structured loans by employing a discounted cash flows method. They delineated the components of LGD (or LIED) such as write-offs, interest drag, cash interest collected, recoveries and some other expense or income events. A clear evidence of bimodal distribution of LGD is reported, which was important finding for modelling credit loss volatility.

Moody's bank loans study (Carty and Lieberman, 1996) comprised a sample of 58 bank loans. Based on secondary market prices for defaulted bank loans they reported an average defaulted bank loan price of 71%. They did not observe a bi-modal distribution, but reported a skewness toward the high end of the price scale. In the same study, the authors measured the recovery rate for a sample of 229 small and medium-sized loans in the US. They reported an average recovery rate of 79% based on the present value of cash flows. Again, the distribution was highly skewed towards the high end of the scale.

Hurt and Felsovalyi (1998) studied the characteristics of C&I bank loan defaults in Latin America and concentrate on bank loss measurement in case of default. For 1149 defaulted bank loans in the 1970 – 1996 period they measured 31.8% average loss in the event of default, which corresponded to 68.2% average recovery rate. They employed discounted cash flow approach. The LGD distribution proved to be highly skewed and reflected a large number of loans with small losses and a small number of loans with losses approaching 100%. Loan size turned out to be important explanatory factor for measured loan losses in the event of default.

Resuming the results of some recent works, Emery (2003) reports some referential values which are of interest to our research. The median RR on secured bank loans is 73.0% and 50.5% on senior unsecured bank loans. Several researches have also presented fairly high variance levels across industrial sectors (Verde, 2003). Schuermann (2004) recently highlighted the importance of the industry factor in determining LGD in a survey of the academic and practitioners literature.

One of the largest and more recent studies that focus on loans to small and medium-sized enterprises was made by Standard & Poor's Risk Solution Department (Franks, Servigny, Davydenko, 2004). It considers collateral as the key driver of recovery rates, which vary across banks within the same country and jurisdiction. Recovery rates also differ across countries where banks respond to different bankruptcy regimes and codes by adjusting different lending practices. In France, for instance, banks demand higher levels of collateral and target specific forms of collateral. The recovery rate in France differs significantly (it is lower) from recoveries in the UK and Germany.

In one of the lately published papers Gupton (2005) applied LossCalc™ Moody's KMV model to predict LGD and employed a dataset which included 1424 defaulted public and private firms. He studied LGD for defaulted loans, bonds and preferred stock for period January 1981 – December 2003 in Australia, New Zealand, Canada, Europe, Latin America, the United States and the United Kingdom, with at least seven years of data in each. The inclusion of any of the transition countries in the research is not reported.

The most recent study on bank loan LGD rates was published by Dermine and Carvalho (2006) who investigated LGD characteristics for 374 corporate bank loans to small and medium size firms in Banco Comercial Portugues over the period 1995 – 2000. The authors applied mortality analysis to defaulted bank loan recovery rates and tested empirically the determinants of recovery rates. Additionally they provided information on the direct costs incurred by a bank in recoveries on bad and doubtful loans. The average recovery rate measured in their study was 71%, which was in line with some earlier studies in the field. More importantly, they showed that the frequency distribution of bank loans' LGD rates proved to be bimodal and in their multivariate analysis of the determinants of loan losses they identified statistically significant explanatory variables such as size of the loan, collateral, industry sector, year dummies and age of the obligor (firm). The work of Dermine and Carvalho (2006) to a large extent also inspired our analysis of bank loan recovery rates.

3. Measurement methods, data and explanatory factors

3.1. Default and loan recovery measurement

We consider a bank borrower (an obligor) as being in default when a payment has been missed for more than 90 days as is recommended by the Basel II capital adequacy rules. Translating this recommendation into loan credit rating system, as enforced by the national banking sector regulator[5], it would mean that every company with a rating worse than or equal to C is shifted into the recovery process.

As no data have been available on the market price of loans as at the default date, we decided to apply the discounted cash flow approach to calculate recovery rates. This approach asks for calculation of the present value of actually recovered cash flows related to each specific loan. Similarly as most other studies (e.g. Asarnow and Edwards, 1995; Carty and Lieberman, 1996) we did not have access to the contractual interest rates charged on individual loans. Therefore we decided to take the average interest rate on Slovenian Tolar denominated loans (as all exposures were tabled in

---

[5] Rating system of the Bank of Slovenia.

SIT) for the 2001-2005 period as an alternative. So the annual discount rate amounted to 10% and included also the workout costs incurred by the recovery proceedings.

In order to measure the cash flows recovered after a default event we tracked the post-default credit balances at the end of each year. Capital recovery is a reduction of the total credit balance. The total cash flow recovered equals the capital recovery plus the interest on the outstanding balance. The tracking of cash flows after a default event appears to be a relatively simple (although time-consuming) exercise, but special cases do require the following adjustments:

- upgraded companies that were shifted back to 'performing' companies were excluded from the model; and

- only those companies and facilities whose recovery proceedings have been closed down or finished are included.

The application of the method used in our analyses was done with some references to the mortality-based approach that was firstly introduced in the study on Portuguese bank loans LGDs by Dermine and Carvalho (2006). It examines the percentage of a bad and doubtful loan which is recovered *n* years after the default date. This methodology is appropriate because the population sample is changing over time.

In order to explain clearly the method, used for measuring loan recovery rates, we provide the next simplified example. Consider a loan of 100 EUR that enters the default category in year one. We track the subsequent payments on this loan, assuming, for expository convenience, that all payments take place at the end of the year. We assume the following time schedule of payments: 50 EUR at the end of year two, 26 EUR at the end of year three and 14 EUR at the end of year four. The discount rate is 10%.

The marginal recovery rate in year t (MRR_t) is defined as the proportion of the outstanding loan, which is repaid in period t (i.e. t periods after the occurrence of the default). Therefore, MRR_t for each repayment period can be calculated as:

$$MRR_t = \frac{[CF_t/(1+r)^t]}{Loan\ outstanding\ at\ the\ time\ of\ default}\ ,$$

where CF_t represents the repayment cash flow in period t and r stands for the discount rate used to calculate the discounted value of the expected future cash flows. In the illustrative example indicated above the marginal recovery rates for three consecutive years would be: $MRR_1 = 0.455$, $MRR_2 = 0.215$, and $MRR_3 = 0.105$

Based on the marginal recovery rate calculation the cumulative recovery rate (CRR_T) can be calculated as: $CRR_T = \sum_{t=1}^{T} MRR_t$. The cumulative recovery rate represents the proportion of the defaulted loan value that has been repaid (in present value terms), T periods after default. In our illustrative example the cumulative recovery rate for the second and third period (year) would be $CRR_{T=2} = 0.669$ and $CRR_{T=3} = 0.775$ respectively.

Finally, the loss given default (*LGD*) can be calculated as $LGD = 1 - CRR_T$. The calculated loss given default may serve as a basis for loan loss provisioning scheme in the bank. Again, in our illustrative example the LGD for the defaulted loan can be calculated as

$$LGD = 1 - CRR_3 = 1 - 0.775 = 22.5 \%,$$

which means that 22.5% of the defaulted loan value (interest payments included) is not expected to be recovered in the future.

Workout costs incurred with loan recoveries represent the important parameter that needs to be accounted for properly in the analysis. Not much of the literature provides information on workout costs. To our knowledge the study by Dermine and Carvalho (2006) represents one of the exceptions in this regard. Following the Dermine and Carvalho (2006) example we report workout costs for corporate loans portfolio in the analysed banking firm (Table 1). The data that refer to the 2002 – 2005 period do not cover the salaries of the department's employees. For reasons of confidentiality, only relative figures are reported in Table 1. We observe that the average costs of proceedings per recovered cash amounts to 0.44%. These costs include the costs of external lawyers' fees and the costs of proceedings at law courts. According to an expert's opinion in the bank, recovery costs on smaller loans in terms of the percentage of recovery are substantially higher than on large loans. The same was reported by Dermine and Carvalho (2006) in their case of the Banco Comercial Portugues. However, excluding the internal costs of employees' salaries within the ARM (asset recovery management) department, the ratio workout cost per fund recovered is relatively low. Therefore we will not go into further details of the workout cost structure in our case study. By adding the salaries of the bank's employees to these costs we can make an approximation of 1-2% of workout costs by exposure and apply these workout costs implicitly in the higher discount rate, which is 10% as mentioned above.

Table 1: Workout costs incurred in Slovenia within the period 2002 – 2005

- in 000 SIT

Corporates and SP	Cost of proceedings			Funds recovered	Ratio Cost/ Recovery (%)
	Fees	Cost of proceedings and expertise	Total		
Total 2002	231,517.5	93,587.7	244,800.5	42,590.3	0.57
Total 2003	172,597.2	- 10,326.5	162,270.8	41,073.4	0.40
Total 2004	98,760.6	13,609.8	112,370.5	33,048.5	0.34
Total 2005	88,297.2	5,066.2	93,363.3	19,490.7	0.48
AVERAGE	167,625.1	32,290.4	173,147.3	38,904.1	0.44

Source: Authors' calculations

3.2. Selection of explanatory variables

In this section we briefly introduce and evaluate the data on 'loss' drivers we have obtained from the bank for corporates in order to define the necessary factors for the model introduced later in the paper. Most of the data we have collected for the purpose of the model construction are annually based (the end of each year) because of the easier grouping of data that are not always fully coherent with other data sources.

Ideally the data for LGD calculations should cover at least one economic cycle completely. For example, according to the requests regarding the LGD estimation in the Basel II capital standard framework, the observation period should not be shorter than seven years for at least one source (Bank for International Settlement, 2004). We encountered problems in fulfilling these requirements as most of our data have only been explicitly tabled since 2001 when a collateral policy came into force and changed their storage within the bank. However, a pivot model for the period from 2001 to 2005 is a good basis to work on and it should then be gradually updated with additional necessary information when available.

The data required to develop LGD models will vary significantly according to the methodology for calculating LGD measures chosen by the bank. It will also depend on specific business practices of banks with respect to taking collateral, i.e. whether specific collateral is attached to a specific facility or whether collateral is kept at the customer level and is available to be allocated across all the customer's facilities.

A comprehensive survey of possible explanatory variables relevant for empirical LGD estimation can be found in Benett et al. (2005). In this paper we focus on four different sets of variables: variables describing the collateralisation of facilities, type

of industry variable, macroeconomic factors and other information contributing to final recovery.

Variables describing the collateralisation of facilities. Carvalho and Dermine (2006) showed in their studies that collateral plays an important role when analysing recoveries on loans. In our case the data describing the collateral features of each facility were gathered from a data source that could be already treated as a data management model. It contains most of the required information (e.g. facility number, collateral number, type of collateral and value of collateral). Moreover, we have to take into account the high possibility that there are facilities with several items of collateral covering them but, on the other hand, there are also examples of the same collateral covering several facilities. The problem occurring with the tabled collateral value is that there is mostly no information on the market value of the available collateral (most often occurred with the expired assignment of receivables).

Type of industry variable. From the data set we obtained from the bank we were able to calculate the average recovery rates for individual industrial sectors. Additionally, the volatility of recoveries among different sectors was estimated. The literature gives inconsistent answers to the question, whether the sector of the borrower has an impact on LGD results. Altman and Kishore (1996) and Verde (2003) reported a fairly high variance across industrial sectors. Araten et al (2004) could not find significant impact of the type of the industry on LGD values for loans.

Macroeconomic Factors. According to the Basel requirements loss severities for certain types of exposures may not exhibit cyclical variability and LGD may not differ from the long-run default-weighted average. However, for other exposures, this cyclical variability in loss severities may be important and banks will need to incorporate it into their LGD estimates (Basel Committee on Banking Supervision, 2004). In contrast to Basel requirements, Asarnow and Edwards (1995) conclude that there is no cyclical variation in LGD concerning loans. In our case the annual GDP growth rates and year of default as macroeconomic determinants have been tested.

Other information contributing to the final recovery. The differentiation between short-term and long-term loans (maturity factor) can represent an important issue when it comes to recoveries as uncertainty rises with loan maturity, which is reflected in loan prices. Credit analysts consider loan's maturity by approving a facility. Debt outstanding at the time of default also seems to be an important factor (Dermine and Carvalho, 2005). The final rating given to a defaulted company before closing the facility and recovery method can also represent information that helps us to calculate recoveries. Regarding the method of recovery there are different costs of collateral realisation or debt reorganisation and liquidation. The bank can assume the standard restructuring/liquidation intensity for certain customers or product types.

3.3. Database

We have included in our sample all the defaulted companies with an average exposure of more than SIT 1,000,000[6]. The sample consists of 305 companies in default[7].

The dataset with all the required information needed for the calculation of LGD consists of 124 companies that defaulted in the period from 2001 to 2004 and were closed down by the end of 2005. According to experts recovery process takes on average 2-3 years before the case is closed down. In our sample of 124 loans the average recovery period is 3 years. The reason we did not take data before 2001 into account was that the data stored on collateral management were insufficient.

All the data used in the sample were collected internally by different bank reports within the risk management division.

Panels A and B of Table 2 reproduce information on the number of defaults per year and on the amount of debt outstanding at the time of default. We observe that the series of 124 default cases is highly skewed towards 2001. 48% of the observed bad loans were defaulted in 2001. The distribution of the debt outstanding is highly skewed towards the low end (small exposures). 61% of the debt exposure involves amounts less than SIT 10,000,000.

In Panel C the various forms of collateral are reported. They have been divided into five groups:

- – financial collateral (bank deposits, securities, bonds);
- – real estate collateral;
- – physical collateral (movables);
- – guarantees and
- – assignments of receivables.

In cases where there are several types of collateral on the same facility we take the primary collateral in terms of liquidity as the preferential collateral type. In 12% of the cases there is no collateral which means that a very large proportion of bank loans are collateralised as opposed to the results in the Portugal study (Dermine and Carvalho, 2006). The most frequent form of collateral used by SMEs is a mortgage (44%). Looking at the cases where there is no collateral (unsecured) on Panel D of Table 2, we can see that most of the unsecured loans are short-term loans. 17% of the short-term loans were totally unsecured compared to only 5% of the long-term loans that are unsecured. Panel E of Table 2 shows the concentration of different forms of

---

[6] Note: € 1 = SIT 239.64

[7] The data gathered for this study do not include any reference to the identity of clients or any other information that according to the Slovenian Banking Law cannot be disclosed.

secured and unsecured bank's exposure in the sample according to the amount of debt outstanding at the time of default. We can see that large exposures are also most frequently secured with one of the forms of collateral.

Table 2: Descriptive statistics for the sample of defaulted loans

	Number of defaults per year	Percentage (%)
Panel A: Year of default		
2001	59	47.6
2002	22	17.7
2003	31	25.0
2004	12	9.7
Total	124	100.0
Panel B: Debt outstanding at the time of default (SIT)*:		
Large	12	9.7
Medium	37	29.8
Small	75	60.5
Total	124	100.0
Panel C: Forms of collateral:		
Financial collateral (bank deposits, securities, bonds)	6	4.8
Guarantees	38	30.6
Physical collateral (movables, others)	6	4.8
Real estate collateral (mortgages)	54	43.5
Assignments of receivables	5	4.0
Unsecured	15	12.1
Total	124	100.0

	Secured	Frequency of secured (%)	Unsecured	Frequency of unsecured (%)	Total
Panel D: Type of loan:					
Long-term	52	95	3	5	55
Short-term	57	83	12	17	69
Total	109		15		124
Panel E: Debt outstanding at the time of default*:					
Large	11	91.7	1	8.3	12
Medium	32	86.5	5	13.5	37
Small	66	88.0	9	12.0	75
Total	109		15		124

Note: * Small: Debt outstanding < SIT 10,000,000, Medium: SIT 10,000,000 < Debt outstanding < SIT 100,000,000, Large: Debt outstanding > SIT 100,000,000

Source: Authors' calculations

Table 3 reports the concentration of default cases in different business sectors and the use of secured/unsecured loans across these sectors. Eleven business sectors have been created with reference to the NACE classification. Default cases are observed in all business sectors, with a concentration in manufacturing (16% of the default cases), wholesale and retail trade (45% of the default cases). A further aggregation, as used in the econometric tests, leads to four activity sectors: real sector (sectors C, F, H, K), manufacturing (sector D), trade (G) and services (E, I, J, M, O)[8]. A quite similar aggregation into the four activity sectors was made by the Portuguese model (Dermine, Carvalho, 2005). Table 3 provides the relative use of secured and unsecured loans at default. Because of the small number of unsecured defaults the distribution across the four aggregated sectors is quite volatile but the portion of unsecured defaults is low in all four groups and does not exceed 22.6% (in the real aggregated industrial sector).

Table 3: Number of defaults by industrial sectors

NACE economic activities	Number of defaults with collateral	Number of unsecured defaults	Number of defaults (total)	Frequency	
C – Mining	1		1	0.8	
D – Manufacturing	19	1	20	16.1	
E – Electricity, gas and water supply	1		1	0.8	
F – Construction	5	1	6	4.8	
G – Wholesale and retail trade	52	4	56	45.2	
H – Hotels and restaurants	7		7	5.6	
I – Transport, storage and communication	4		4	3.2	
J – Financial intermediation	4		4	3.2	
K – Real estate	11	6	17	13.7	
M – Education	1	2	3	2.4	
O – Other service activities	4	1	5	4.0	
Total	109	15	124	100	
Aggregated industrial sectors	Number of secured defaults	in %	Number of unsecured defaults	in %	Total
Manufacturing	19	95.0	1	5.0	20
Real	24	77.4	7	22.6	31
Services	14	82.3	3	17.6	17
Trade	52	92.9	4	7.1	56
Total	109	87.9	15	12.1	124

Note: Aggregated sectors consist of the following sectors according to European Union's economic activity codes (NACE): Real (sectors C, F, H, K); Manufacturing (sector D), Trade, (sector G), Services (sectors E, I, J, M, O).

Source: Authors' calculations

---

[8] The grouping is made in accordance with the information important for the bank and does not necessarily match the name of the aggregated activity sector.

In Table 4 we report the 1-, 2-, 3- and 4-year cumulative recovery rates for the total sample.

Table 4: Sample unweighted cumulative recovery rates

- in percent (%)

	1-year cumulative recovery	2-year cumulative recovery	3-year cumulative recovery	4-year cumulative recovery
Mean	0.48	0.62	0.70	0.73
Median	0.50	0.88	0.91	0.91
Standard Deviation	0.41	0.40	0.36	0.35
Minimum	0	0	0	0
Maximum	1	1	1	1

Note: Cumulative recovery rates are calculated for the total sample of 124 facilities taking them all at a time. We focus on the time factor of recoveries of the loans in the sample not taking into account the duration of resolution proceedings. This information tells us that 1 year after a default occurs on average 48% of the sample's exposure at default was recovered, 2 years after a default on average 62% of the sample's facility exposure was recovered etc.

Source: Authors' calculations.

On average the biggest portion of recovery was gathered in the first year after a default and is decreasing each year. The mean cumulative recovery rate of 73% (48-month cumulative recovery) is of the same order of magnitude as those reported by Asarnow and Edwards (1995) and Hurt and Felsovalyi (1998) for Latin America. It is also of the same order of magnitude as reported by Dermine and Carvalho (2006).

3.4. Analysis of the determinants affecting recovery rates

First, it is of interest to analyse the distribution of cumulative recovery rates across the sample of loans. The distribution of cumulative recovery rates is reproduced in Figure 1. This figure shows a bimodal distribution with many observations with a low recovery and many with an almost complete recovery (more than 50% of the cases having recoveries between 90% and 100%). These results are quite similar to those reported by Dermine and Carvalho (2006), Asarnow and Edwards (1995) and Schuermann (2004) for the US, and Hurt and Felsovalyi (1998) for Latin America. All these studies find a bimodal distribution of recoveries.

The loan portfolio models that incorporate a probability distribution for recovery rates should take this bimodal distribution into account.

Table 5 provides bivariate relations between LGD and its determinants. Panel A of table 5 indicates the value-weighting effect on cumulative recovery rates. Considering formula LGD=1–RR we can observe that smaller exposures have on

Figure 1: Sample distribution of cumulative recovery rates
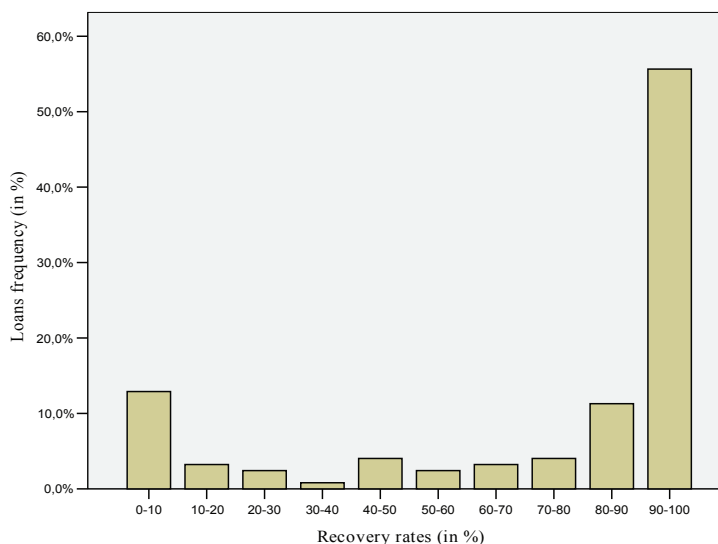
Source: Authors' calculations

average higher losses (almost 30%) in comparison to large exposures (22%), which usually also means bigger companies. This leads to different conclusions from those made by Dermine and Carvalho (2006). The reasons for this can be found in the worse collateralisation of small loans compared to large loans, which can also be seen in the tables in the previous section describing the sample database.

According to the literature mentioned herein, the most important determinant for calculating LGD is the collateralisation of each facility. Banks consider this when pricing a loan. Providing more valuable collateral may help reduce the interests one pays.[9] If one's rating is relatively poor, collateral may help in getting a loan. It pays to inquire what types of collateral one's bank is willing to accept. Note that banks are very conservative in estimating the value of collateral as it is difficult to assess the actual recovery value in case of default and since it requires a considerable effort by the bank to sell collateral to recover loan losses. The impact of collateral on reducing the risks of a loan depends on its type and liquidity (European commission, 2005).

---

[9] The bankruptcy law and its influence on creditors' rights can seriously affect the priority of claims and the proceeds of collateral that accrue to the secured lender. Slovenia represents a special case with its own bankruptcy law and it therefore cannot be directly compared with other countries' laws, e.g.: the collateral level in France tends to be higher than the level in Germany or the UK (Franks, Servigny, Davydenko, 2004, p. 70). In particular, French banks respond to a creditor-unfriendly bankruptcy code by requiring more collateral than lenders elsewhere, and by relying on particular collateral forms that minimise the statutory dilution of their claims in bankruptcy (Davydenko and Franks, 2005, pp. 1-3).

Table 5: Bivariate relations between LGD rate and its determinants

	Average of LGD	Frequency of recovery method (%)
Panel A: Debt outstanding at the time of default (SIT)*:		
Large	0.218	
Medium	0.231	
Small	0.298	
Panel B: Forms of collateral:		
Assignment of receivables	0.604	
Guarantees	0.280	
Real estate collateral	0.236	
Financial collateral	0.139	
Physical collateral**	0.093	
Panel C: Last rating***:		
C	0.146	
D	0.223	
E	0.441	
Panel D: Aggregated industrial sectors****		
Trade	0.288	
Real	0.282	
Services	0.257	
Manufacturing	0.211	
Panel E: Recovery method*****		
Debt rescheduling along execution process	0.540	2
Liquidation proceedings (bankruptcy)	0.455	6
Non-judicial foreclosure or execution	0.369	3
Others	0.354	44
Sale of claims to a third party	0.226	7
Regular repayments	0.196	12
Repayments arrangement with a discount for a client	0.124	6
Repayment arrangement with a client (mostly in one instalment)	0.116	13
Repayment from court auction sale	0.092	2
Debt rescheduling – not in execution process	0.058	3
Informal workout	0.055	2

Note: * Small: Debt outstanding < SIT 10,000,000, Medium: SIT 10,000,000 < Debt outstanding < SIT 100,000,000, Large: Debt outstanding > SIT 100,000,000

** Physical collateral is unusually low

*** Rating system of the Bank of Slovenia

**** aggregated sectors consist of the following sectors according to European Union's economic activity codes (NACE): Real (sectors C, F, H, K); Manufacturing (sector D), Trade (sector G), Services (sectors E, I, J, M, O).

***** Method Formal rehabilitation (reprogramming) was excluded due to the unrepresentative sample (just one case in the sample).
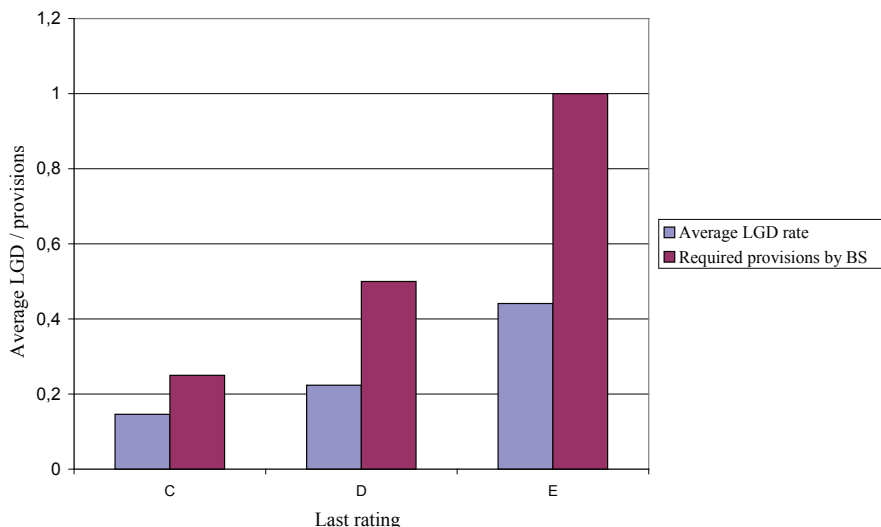
Source: Authors' calculations

Panel B of table 5 presents the average LGD rates regarding the different securitisation types. The assignment of receivables as one of the important collateral types used by Slovenian banks has proven to be very inefficient collateral. The results are not surprising since collectors usually manage to collect very few sources from the assignment of receivables and have more costs than profit arising from it. The contracts usually prove to be out-of-date and very ineffective. We can find reasons in bad collateral management in banks especially in terms of the assignment of receivables. Financial collateral is, according to the results, expected to be the safest type of collateral, excluding the unusually low losses on physical collateral.

The explanatory factor "last rating" was included as a determinant as we can see considerable changes in losses depending on the last rating given to the obligor by credit analysts. Banks use ratings as the main input for calculating the expected loss implied by a given loan. In addition, the required share of the capital to be set aside to take into account the possibility that losses will be higher than expected will also depend on the rating. Thus, the rating is the key indicator of the cost a bank incurs for a given loan and it was taken as a predictor in LGD. The losses ascend in accordance with worse ratings, ranging from a 15% average loss on those exposures rated C to a 44% average loss on those exposures having a rating E as we can see in Panel C of Table 5. The results can be compared with the risk coverage in the portfolio of the Bank of Slovenia as well as in the case of the particular bank. We can observe that the loan loss provisions for ratings C, D and E, which are treated as signs of bad debt, are substantially higher than those observed in our results. Figure 2 presents the difference between the average LGD rate by last rating and loan loss provisions by the rating required by the Bank of Slovenia.

The explanatory factor "aggregated industrial sector" is another important factor of risk calculation. This predictor is a derivative of a fully-segmented factor of industrial activity by NACE. Panel D of Table 5 reports that loans in the trade sector (Sector G) experience the highest risk of having a loss after facing a default (29%). Manufacturing (Sector D) seems to be the safest economic activity from the creditor perspective of the obligor's repayments after a default occurs (21%).

Figure 2: Average LGD rates by last rating and loss provisions by rating required by the Bank of Slovenia

Source: Authors' calculations

Another explanatory factor that can explain to what extent the average loss on one's facility may be expected is the method by which the recovery process is executed. Panel E of Table 5 presents the frequency of methods and what are the average results in terms of loss by each of the methods. According to the sample, the most frequent method noted is the method 'others' (44%), following by a repayment arrangement with the client (13%) and regular repayments (12%). From the same panel we also observe the highest average losses by the methods debt rescheduling along execution process (54%) followed by liquidation proceedings (bankruptcy) where we can expect a loss of 45%. Informal workout and debt rescheduling without an execution process bring the most favourable results with the lowest average losses for the bank in terms of recoveries. Also repayments from a court auction sale, where mortgages as collateral are sold, testify that the collateral-type mortgage reflects a good quality securitisation.

The loan's maturity is another important factor in calculating the price of a loan. It is taken into account by almost all banks. Commonly, interest rates are lower for short-term loans than for long-term ones due to lower uncertainty (European Commission, 2005, p. 24). What we can see from the empirical results in Table 6 is that there are higher average losses on short-term loans no matter they are secured or not (30% on short-term against 23% on long-term ones). We also see the effect of collateral by having lower average losses by secured loans (26%) than by unsecured loans (38%). To find the reasons for different losses between short- and long-term loans we have to make a thorough review of the sample by type of loan (see Table 7). Considering

the sample's average LGD rate by type of loan in terms of the amount of the debt outstanding at the time of default and the loan's maturity (short-term or long-term), both in relation to a facility's collateralisation, we highlight the following conclusions:

- Short-term loans experience higher losses due to worse collateral types (especially the assignment of receivables – 60% average LGD).
- Real estate collateral seems to be relatively effective collateral with the average recoveries being quite similar for either short-term or long-term loans (23% average LGD).

Table 6: Average LGD rate by maturity of loan (type of loan) and by securitisation

Securitisation	Type of loan		Total
	Long-term	Short-term	
Secured	0.215	0.291	0.255
Unsecured	0.537	0.338	0.378
Total	0.233	0.299	*0.270*

Source: Authors' calculations

Financial collateral as one of the primary collateral types (deposit or any kind of securities) is limited for large exposures where its value represents just a certain percentage of the exposure. Usually there is another type of collateral combined with financial collateral for the same facility. Large exposures are also often long-term ones and therefore we witness larger losses in the long-term where financial collateral is the primary collateral.

In the following two sections the empirical model and the estimation results are presented.

Table 7: Average LGD rate by type of facility

		Securitization						
		Assignment of receivables	Unsecured	Guarantee	Real estate collateral	Financial collateral	Physical collateral	Average LGD by type of loan
Exposure size	Large		0.068	0.880	0.045	0.416	0.050	0.218
	Medium		0.504	0.245	0.185	0.089	0.000	0.231
	Small	0.604	0.342	0.247	0.328	0.079	0.127	0.298
Maturity	Long-term loan		0.537	0.158	0.237	0.199	0.117	0.233
	Short-term loan	0.604	0.338	0.308	0.232	0.078	0.045	0.299
Average LGD by type of collateral		0.604	0.378	0.280	0.236	0.139	0.093	*0.270*

Source: Authors' calculations

4. Empirical model

In the case of modelling recoveries our dependent variable is a continuous variable over the interval [0, 1]. Taking into account this as well as some other boundaries, we have to look for an alternative from ordinary least square (OLS) regression. McCulagh and Nelder (1989) use a transformation of this interval onto the whole real line by a common econometric technique. On the other hand, instead of this method we can define our dependent variable as an ordinal variable by grouping our recovery interval [0, 1] into several ordinal categories.

Generalised linear models (GLMs) are used to do regression modelling for non-normal distributed data with a minimum of extra complications compared with a normal linear regression. They are flexible enough to include a wide range of common situations but at the same time allow most of the familiar ideas of normal linear regression to carry over. We can use it to predict responses for both dependent variables with discrete distributions and for dependent variables which are nonlinearly related to the predictors.

To summarise the basic ideas, the generalised linear model differs from the general linear model (of which, for example, multiple regression is a special case) in two major respects (McCullagh, Nelder, 1989).

First, the distribution of the dependent or response variable can be (explicitly) non-normal and does not have to be continuous. It can be binomial, multinomial or ordinal multinomial (i.e., contain information on ranks only), and

Second, the dependent variable values are predicted from a linear combination of predictor variables which are connected to the dependent variable via a *link function*.

The relationship between a response variable Y and independent variables X in the GLMs is assumed to be:

$$Y = g\,(b_0 + b_1X_1 + b_2X_2 + ... + b_kX_k + e)$$

where e denotes the error term, and g(.) is a function. Formally, the inverse function of g(.), say f(.), is called the link function, so that:

$$f(mu_y) = b_0 + b_1X_1 + b_2X_2 + ... + b_kX_k$$

where mu_y stands for the expected value of y.

The basic form of a GLM can also be written as an ordinal regression in the following way (SPSS Advanced Models 10.0):

$$link(\gamma_j) = \theta_j - (\beta_1x_1 + \beta_2x_2 + \ldots + \beta_kx_k)$$

where γ_j is the cumulative probability for the *j*-th category, θ_j is the threshold for the *j*-th category, $\beta_1 \ldots \beta_k$ are the regression coefficients, $x_1 \ldots x_k$ are the predictor variables, and *k* is the number of predictors. Link(γ_j), meaning link function, is a transformation of the cumulative probabilities that allows an estimation of the model.

The goal of the ordinal regression analysis is to model the dependence of a polytomous ordinal response on a set of predictors, which can be factors or covariates.

5. Results

5.1. Estimation results and interpretations

In Table 8 we report the empirical results for the base case of the ordinal regression. In our model the higher recovery categories were more probable and we had many extreme values, thus the link functions of Complementary log–log and Cauchit (inverse Cauchy) were selected to run the ordinal regression analysis of our models. The base case uses inverse Cauchy link function, which is defined as follows:

$$\tan \left(\Pi \left(\gamma - 0.5 \right) \right) = \theta_j - \left(\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \right)$$

After having identified the dependent variable of the model, which in the base model we divided into five classes ranging from 0 to 100% recovery, we also tested all the explanatory variables for the location component of the model. A preliminary exploratory analysis, already presented in previous sections, was undertaken in order to identify the likely explanatory variables. The next step consists of empirical considerations to evaluate the importance of each variable. All of the dependent variables in the model (primary collateral type, sector of industry; type of loan, last rating, size of the debt outstanding at the time of default, recovery method, GDP growth and year of default) are included as factors since they are all categorical variables. In the base model we chose the location-only component assuming that the scale component is not necessary and as such the location-only model provides a good summary of the data.

The difference of log-likelihoods can be usually interpreted as chi-square distributed statistics (McCullagh, Nelder, 1989). The significant chi-square statistics indicates that the model gives a significant improvement over the baseline intercept-only model. This basically tells us that the model gives better predictions than if we merely guessed on the basis of marginal probabilities for the outcome categories.

Due to the relatively small population of the available data we were constrained to make aggregations of the groups on some explanatory nominal variables mentioned herein. With more segmented variables we increase our determinant coefficients in the regression, but the model is only 'artificially' better as this coefficient is not

corrected by the number of degrees of freedom. The significant Pearson's chi-square indicates that the data and the model predictions are similar and that we do have a good model. These statistics can be sensitive to empty cells so we tried to reduce the empty cells by grouping the explanatory variables as in the case of an aggregated industrial sector.

The estimated parameters for the individual explanatory variables in the model are displayed in Table 8. We focus on location parameters which relate the predictor variables to the cumulative recovery category probabilities.

In our model, the Nagelkerke's Pseudo R-square is respectable with values around 0.36 as we can observe in Table 8. It is expected for this type of analyses since there is a large variation in recovery rates and we are limited with our set of explanatory variables.

For location-only models, the test of parallel lines can help us assess whether the assumption that the parameters are the same for all categories is reasonable. This test compares the estimated model with one set of coefficient for all categories to a model with a separate set of coefficients for each category j (SPSS Advanced Models 10.0):

$$\text{link}(\gamma_j) = \theta_j - (\beta_{1j}x_1 + \beta_{2j}x_2 + \ldots + \beta_{kj}x_k)$$

We can see that the general model (with separate parameters for each category) gives a significant improvement in the model fit (see Table 8). We cannot assume that the values of the location parameters are constant across the categories of the response. We can change the model by adding one of the predictive factors as a scale component (e.g. size of the debt outstanding at the time of default). Scale component is an optional modification to the base model to account for differences in variability for different values of the predictor variables.

The model with a scale component follows the form (SPSS Advanced Models 10.0):

$$\text{link}(\gamma_j) = \frac{\theta_j - (\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k)}{\exp(\tau_1 z_1 + \tau_2 z_2 + \ldots + \tau_m z_m)}$$

Where $\tau_1 \ldots \tau_m$ are coefficients for the scale component and $z_1 \ldots z_m$ are m predictor variables for the scale component (scale from the same set of variables as the x's). By the new alternative model we also achieve a better prediction power. On the other hand we can also resolve the problem of parallelism by distributing our dependent variable into unequally distributed classes of recovery rate (e.g. 0-50%; 50-90%, 90-100%). By doing so, the test of parallel lines results to the assumption that the location parameters are constant across the categories of response.

This type of model provides the best fit to the data and enables us to get insight into the characteristics of the recovery rates' explanatory factors (Table 8).

According to the statistical tests, most of the explanatory variables included in the model model seem to be important. Due to the minimisation of the number of explanatory variables, the aim of which is to have a statistically correct model, we excluded the recovery method, GDP growth and year of default from the base model.

The first observation is that, as expected, the collateral variables (real estate, physical) have a statistically significant positive effect on the cumulative recovery at a significance of 0.05. Financial collateral also has a positive effect. As was the case of the univariate figures (although not statistically significant), the assignment of receivables has a negative effect on the cumulative recovery.

The aggregated industrial sector dummies are significant and positive in most cases and confirm the observation that recoveries in the aggregated sector 'trade' (the base case) are lower than the other four aggregated industrial sectors.

The next observation to confirm our empirical analysis of the cumulative recovery rates was the last rating. A better rating also brings higher recoveries.

The sign of coefficients for the explanatory variable 'the size of the debt outstanding at the time of default' gives us another important insight into the effects of the predictors in the model. Positive signs (although not statistically significant at p=0.05) indicate that recoveries are higher with larger exposures, confirming our observation in the empirical analysis and the sample univariate weighted and unweighted average cumulative recovery rates.

Finally, the model shows a statistically significant negative sign for a long-term loan. This indicates an inverse relationship with the dependent variable. A long-term loan is on average expected to fall into a lower recovery category than a short-term one, which means a lower level of recovery.

Given the large number of explanatory variables and model variations, alternative specifications were excluded from the reporting in this paper. As indicated above, additional explanatory variables have been tested: recovery method, annual GDP growth and year of default. None of these variables were significant due to dataset boundaries, namely small dataset and high skewness towards the companies defaulted in 2001 reasoned by the closing recovery process effect in our database. Additionally, in the 2001 – 2005 period the economic conditions have been very much in favour of economic growth, we cannot capture a real 'downgrade LGD' during that time. In the observed period the economy did not experience any important shocks that could also negatively impacted the LGD results. On the contrary, the economy flourished which also resulted in lower losses.

Table 8: Empirical results of the ordinal regression

Parameter estimates					
		Estimate	Std. Error	Wald	Sig.
Threshold	Recovery 0-20%	1.18	0.821	2.069	0.15
	Recovery 20-40%	1.608	0.831	3.743	0.053
	Recovery 40-60%	2.334	0.897	6.769	0.009
	Recovery 60-80%	3.001	0.979	9.39	0.002
Location	Assignment of receivables	-0.854	1.18	0.524	0.469
	Financial collateral	2.82	1.729	2.659	0.103
	Personal guarantee	0.729	0.643	1.288	0.256
	Physical collateral	4.621	1.658	7.77	0.005
	Real Estate collateral	3.856	1.213	10.109	0.001
	Unsecured	0(a)	.	.	.
	2.Manufacturing	1.475	0.699	4.458	0.035
	3.Real	1.806	0.752	5.777	0.016
	4.Service	1.188	0.777	2.339	0.126
	5.Trade	0(a)	.	.	.
	Long-term loan	-2.637	0.92	8.225	0.004
	Short-term loan	0(a)	.	.	.
	Last rating C	3.856	0.983	15.379	0
	Last rating D	2.19	0.886	6.106	0.013
	Last rating E	0(a)	.	.	.
	Exposure at default = Large	0.605	0.844	0.514	0.473
	Exposure at default = Medium	0.929	0.555	2.801	0.094
	Exposure at default = Small	0(a)	.	.	.
	Model	-2 Log Likelihood	Chi-Square	df	Sig.
Model-fitting information					
	Intercept Only	218.095			
	Final	170.696	47.399	13	0.000
Goodness-of-fit table					
Pearson				333.194	287	0.031
Deviance				141.081	287	1
Test of parallel lines					
	Null Hypothesis	170.696			
	General	81.846(b)	88.850(c)	39	0.000
Pseudo- R^2 measures					
	Cox and Snell	0.318			
	Nagelkerke	0.363			
	McFadden	0.184			

Link function: Cauchit

a. This parameter is set to zero because it is redundant.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

Source: Authors' calculations

5.2. Predictions

For each case, the predicted outcome category is simply the category with the highest probability given the pattern of the predicted values for that case. For example, suppose we have a small (debt outstanding at the time of default) short-term (type of loan) loan from a client in the industrial sector "trade", having financial collateral as securitisation and being finally rated C, then the model gives the following individual category probabilities:

– recovery 0-20%: 0.06;
– recovery 20-40%: 0.00;
– recovery 40-60%: 0.01;
– recovery 60-80%: 0.01 and
– recovery 80-100%: 0.92.

Clearly, the last category with the highest recovery is the most likely category for this case according to the model, with a predicted probability of 0.92. We thus predict that this facility will be successfully recovered. For the sake of being focused on LGD determinants and their correlation to dependent variable the prediction and classification tables are not reported in the paper.

5.3. Robustness tests

Two types of robustness tests have been conducted. The first test was a random selection of 90% of the observations. The results in terms of coefficients' signs are consistent with those of the specifications in the original tests and so with those of the base specifications, confirming the statistical significance of the loan collateralisation, the last rating, the type of loan, and of the same significance level by the type of industry and size effect.

In the second test we wanted to ensure that the size effect was not driven by high recoveries relative to a few large loans so we eliminated the 10% largest loans from the sample. The results were again consistent with the results of the original model and the base specifications. For the sake of space, the estimated parameters are not reported here.

6. Conclusions

In this paper we estimate the LGD parameter for a typical loan portfolio consisting of SME loans in a commercial bank operating in Slovenian banking market. In most of the literature the LGD estimates are approximated and analysed by the use of the corporate bonds market data. However, we set a hypothesis that in the absence of the

bond market data reliable LGD estimates can be obtained by using the discounted cash flow approach. We verify the reliability of LGD estimated by identifying and confirming the significance of the following explanatory factors: type of collateral, type of the industry, last available loan rating, recovery method and size of the loan exposure. Additionally we found that the frequency distribution of loan LGD appears bimodal with many cases presenting recoveries close to 0% and a concentration of other cases presenting high recoveries from 80 to 100%.

In generalisation of our findings a precaution is necessary, since the data used in the analysis could reflect the idiosyncrasies of the specific bank's SME loan portfolio. By broadening the sample of loans to all corporate exposures the robustness of findings could be enhanced and relevance of the results strengthened.

We clearly demonstrate that reliable LGD estimates can be produced by alternative although not necessarily extremely sophisticated methodological solutions. This kind of investigation that enables us to analyse the LGD explanatory factors can significantly improve the credit risk management process in a bank, which includes the impairment policy determination and capital adequacy calculation. Both aspects of credit risk management process are especially important in developing banking markets as most of the markets in Southern and Eastern Europe are. By adding a richer set of the data into the LGD calculations, gathered from an efficiently run risk data warehouse, banks could develop a powerful credit risk management tool that could represent an important source of comparative advantage. The research to follow in the academic literature can also further contribute to the methodological advances in the field and lead the way to even more effective risk management solutions in banks, which has proved to be one of the corner stones of sound and stable banks.

References

Altman, E.I. and V.M. Kishore (1996) "Almost Everything You Wanted to Know About Recoveries on Defaulted Bonds", *Financial Analyst Journal*, November/December, Vol. 52, Issue 6, pp. 57-64.

Altman E. I., Resti A., Sironi A. (2005) *Recovery Risk: The next Challenge in Credit Risk Management*, London: Risk Books.

Araten M., Jacobs M., Varshney P. (2004) "Measuring LGD on Commercial Loans: An 18-Year Internal Study", *The RMA Journal*, May, pp. 28-35.

Asarnow E., Edwards D. (1995) "Measuring Loss on Defaulted Bank Loans: a 24-Year Study", *The Journal of Commercial Lending*, Vol. 77, No. 7, pp. 11-23.

Bank for International Settlement (2004): *International Convergence of Capital Measurement and Capital Standards, A Revised Framework*; Basel Committee on Banking Supervision. Basel: Bank for International Settlement.

Bank of Slovenia (2007): *Financial Stability Review*, Ljubljana, Bank of Slovenia, Eurosystem.

Bank of Slovenia (2009): *Financial Stability Review*, Ljubljana, Bank of Slovenia, Eurosystem.

Benett R.L., Catarineu E., Moral G. (2005) "Loss Given Default Validation". In: Basel Committee on Banking Supervision, *Studies on the Validation of Internal Rating Systems*, Working Paper No. 14, Bank for International Settlement, pp. 60-93.

Carty L. and Lieberman D. (1996): *Defaulted Bank Loan Recoveries*. Moody's Investors Service, November.

Crouhy M., Galai D., Mark R. (2000) "A Comparative Analysis of Current Credit Risk Models", *Journal of Banking and Finance*, Vol. 24, pp. 59-117.

Davydenko S. and Franks J. (2005) *Do bankruptcy codes matter? A study of defaults in France, Germany and the UK*, London : London Business School.

Dermine J. and Carvalho C. (2006) "Bank Loan Losses-Given Default. A Case Study", *Journal of Banking and Finance*, Vol. 30, pp. 1219-1243.

Emery K. (2003) *Moody's Loan Default Database as of November 2003*. Moody's Investors Service, December.

European Commission (2005): *How to deal with the new rating culture. A practical guide to loan financing for small and medium-sized enterprises*. Brussels: European Commission.

Franks J., Servigny A. and Davydenko S. (2004): *A comparative analysis of the recovery process and recovery rates for private companies in the U.K., France, and Germany. Standard & Poor's Risk Solutions Report*. New York: Standard & Poor's Risk Solutions.

Hurt L. and Felsovalyi A. (1998) "Measuring Loss on Latin American Defaulted Bank Loans, a 27-Year Study of 27 Countries", *The Journal of Lending and Credit Risk Management*, Vol. 80, pp. 41-46.

McCullagh P., Nelder J.A. (1989) *Generalized Linear Models. Monographs on Statistics and Applied Probability 37*, Boca Raton : Chapman & Hall/CRC. 540 p.

Schuermann T. (2004) *What Do We Know About Loss Given Default?* New York: Federal Reserve Bank of New York.

SPSS (1999) *SPSS Advanced Models 10.0*, Chicago: SPSS Inc.

Verde, M. (2003) *Recovery Rates Return to Historic Norms* Fitch Ratings, September.

"Loss given default" determinante kredita u komercijalnim bankama: primjer tržišta u razvoju

Marko Košak[1], Jure Poljšak[2]

Sažetak

Svrha ovog rada je analizirati determinante gubitaka u slučaju neplaćanja (loss given default ili LGD) za tipičan kreditni portfelj koji se sastoji od kredita malim i srednjim poduzećima, u poslovnoj banci koja djeluje na jednom od brzo razvijajućih bankarskih tržišta, tj. u Sloveniji. Precizne LGD procjene "defaultiranih" bankarskih potraživanja važne su za određivanje potrebnih rezervi za kreditne gubitke, dalje za izračunavanje odgovarajućeg rizičnog kapitala i određivanja fer cijene rizičnih bankovnih kredita. Dok se većina empirijske literature na području koncentrira na tržište korporativnih obveznica u svrhu procjene gubitka u slučaju neplaćanja, u našoj studiji koristimo jedinstveni skup podataka pojedine banke o MSP kreditima i na te kredite vezane gubitke. Zbog vlasničke prirode podataka, dosad je u svijetu objavljivano samo nekoliko studija ove vrste. Prema našem znanju ni jedna od tih studija ne pokriva istočnoeuropska bankarska tržišta. U prvoj fazi analize procjenjujemo LGD parametar primjenom pristupa diskontiranog novčanog toka, dok u drugoj fazi analiziramo njegove LGD determinante pomoću ordinalne regresijske analize. Naši nalazi pokazuju da pouzdane procjene LGD parametra mogu biti proizvedene diskontiranjem očekivanih budućih novčanih tokova koji se odnose na kredite. Objasnidbeni čimbenici, kao što su vrsta osiguranja, vrsta industrijskog sektora, posljednji dostupan kreditni rating, veličina duga i dospijeće kredita, zadovoljavajuće pojašnjavaju varijabilnost LGD parametra na određenom bankarskom tržištu. Rezultati nisu samo relevantni za određivanje politike umanjenja vrijednosti potraživanja banke i za izračun adekvatnosti kapitala u određenoj banci, nego i za procjenu karakteristika MSP kredita na tržištima u razvoju.

Ključne riječi: *banka, krediti malim i srednjim poduzećima, gubitak u slučaju neplaćanja (LGD)*

JEL klasifikacija: *G21, G32*

[1] *Izvanredni profesor, Sveučilište u Ljubljani, Ekonomski fakultet, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenija. Znanstveni interes: bankarstvo, financije. Tel.: +386 1 5892 561. E-mail: marko.kosak@ef.uni-lj.si. Osobna web stranica: http://www.ef.uni-lj.si/pedagogi/pedagog. asp?id=147*

[2] *Financijski analitičar poduzeća, Abanka Vipa d.d., Slovenska cesta 58, 1000 Ljubljana, Slovenija i suradnik istraživačkog projekta na Sveučilištu u Ljubljani, Ekonomski fakultet, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenija. Znanstveni interes: financije. Tel.: +386 1 4718 100. E-mail: jure.poljsak@abanka.si*