Loss Given Default on a medium-sized Italian bank's loans: an empirical exercise

Francesca Querci*

January 2005

Abstract

On the grounds of data provided by an Italian medium-sized commercial bank, this paper examines Loss Given Default, that is the portion of defaulted loans the bank is able to recover, going through the entire workout process. The sample includes 15,827 loans, from 1980 to half 2004, which are analysed according to the borrowers' settlement area, the borrower segment, the security, the loan form, the length of the collection process. We analyse the sample as a whole and also subsets of data in order to identify what are the most influencing variables on LGD.

Keywords: loss given default; bank; loans

JEL Classification Numbers: G21

* Ph.D. student at Genoa University

Introduction

Loss given default (LGD), which represents the credit loss incurred if a bank's borrower defaults, is a key component of the expected loss on a single exposure or on a loans portfolio. Actually, the expected loss results from the probability of default and from the loss in the event of default. A bank can only make an estimate of LGD, since it is a random variable, open to fluctuations which can lead to an unexpected loss.

The New Basel Capital Accord[1], expected to be implemented at year-end 2006, allows banks to determine LGD according to their own internal measurements.

The first problem a bank has to face, concerns the availability of information: more precisely, an estimation model for LGD must be based on long term historical data[2] and much information lies in papers or in databases which are not able to share data with each other. Banks must collect all necessary information and record it in an integrated database and this requires a considerable effort.

This paper presents LGD estimations based on the banking book of an Italian medium-sized bank, which operates as a financial conglomerate and has widely developed the number of its domestic branches; its shares are quoted on the Blue Chip, the equity share market segment that includes companies with a capitalisation above 800 million euros.

On the grounds of these data, we will try to answer to the following questions:
- How does LGD distribution appear?
- Is LGD distribution different according to the borrowers' settlement area, to the borrower category, to the loan form, to the security level and to the workout process's length?
- What drives LGD variation? Are driving forces different according to the above-mentioned aspects?

As to the structure of our paper, the first part gives a definition of LGD according to the more recent empirical studies, both international and domestic; the second part describes the sample's composition; in the third part we try to give an answer to the above issues and we draw down some conclusions.

1. The definitions of Loss given default in the most recent literature

Available empirical analyses on Loss given default are relatively recent, moreover there is not an univocal methodology for the determination of this parameter. Actually, there are two main measures: the so called "market LGD", which is based on market prices of defaulted bonds or marketable loans, observed soon after the default event[3], and "workout LGD", which is measured on the grounds of discounted cash flows resulting from the collection process, after expenses.

---

[1] Basel Committee on Banking Supervision (2004).
[2] The minimum data observation period for LGD estimates is seven years (five years for retail exposures years). See § 472-473 Basel Committee on Banking Supervision (2004), *ibid.*
[3] Moody's dataset includes prices observed one month after the default event: a shorter period would not allow the market to assimilate and to accurately assess the occurrence, while a longer period could dilute its effect over the time and it could be misleading.

Main studies about market LGD are: Altman, Brady, Resti, Sironi (2003); Hamilton et al. (2003); Varma et al. (2003); Katzengruber (2003) ; Schuermann (2003); Renault, Scaillet (2003); Gupton (2003); Gupton, Stein (2002); Hamilton, Cantor, et al. (2002); Hamilton, Cantor, Ou (2002); Gupton, Gates, Carty (2000); Frye (2000); Fridson (2000a) and (2000b); Carty, Hamilton (1999); Carty, Hamilton, et al. (1998); Carty, Lieberman (1996); Altman, Kishore(1996); Eberhart, Sweeney (1992).

Most studies about LGD are based on price recoveries, which have several advantages: first of all, they are easy to measure; moreover, for investors who decide to liquidate their defaulted positions immediately after default, the observed prices actually represent the recoverable portion of their credit; finally, they do not require the choice of a specific discount rate.

On the other hand, price recoveries are very sensitive to supply and demand issues: the market may not be able to absorb very large quantities of defaulted securities in a short period of time and this may influence their price[4]. Finally, they tend to show significantly lower means than discounted recoveries[5].

Therefore, "workout LGD" is a more suitable estimation for a bank which goes through an entire collection process, sustaining the financial cost related to the process's length, besides the workout expenses. Moreover, results deriving from price recoveries cannot be extended to the European context, where a liquid and wide loans secondary market does not exist yet.

From now on, we will refer to LGD as the one determined as follows:

$$1 - \frac{\text{discounted workout recoveries} - \text{workout expenses}}{\text{bank's exposure at the moment of default}}$$

where recoveries include principal and interest payments and cash flows deriving from the liquidation of possible collaterals.

Empirical evidence based on the above-mentioned LGD definition is very limited in number and results are not always comparable, because of the differences in the adopted discount rate or in the computed components.

As to the first aspect, discounting is usually made by applying the interest rates' maturity structure, referred to the beginning (month and year) of collection process. On the contrary, Asarnow, Edwards (1995) has chosen the average interest rate on the loans of the analysed bank, while Lazzari, Laruccia (2002) have applied the investigated bank's prime rate.

Referring to the components included in the computation, Carty, Lieberman (1996) do not deduct workout expenses from recoveries; moreover, in its survey on the entire Italian banking system[6], the Bank of Italy states that not all respondents have been able to specify the collection costs. Still referring to the Italian context, Lazzari, Laruccia (2002) do not include either fixed costs or overdue interest in their measurement.

With reference to the sample considered in this study, all components have been included in the LGD estimation, but it is necessary to specify a peculiarity regarding workout expenses: at the moment, the examined bank is not able to specify costs by collection procedure, but by borrower on the whole; therefore, these costs have been ascribed to each recovery process in proportion to the exposure amount.

Let us observe the sample structure and discover our LGD's features.

---

[4] Renault, Scaillet (2003), *op.cit.*
[5] For an in-depth study about the differences between price recoveries and workout recoveries, see Katzengruber (2003), *op.cit.*
[6] See Banca d'Italia (2001).

2. The sample structure

The investigated sample is composed by 15,827 loans, disbursed by an Italian medium-sized commercial bank, to domestic borrowers. These loans were classified as "doubtful debts" from March 1980 and their collection processes were closed within August 2004. This bank has determined a preliminary estimation of LGD, based on the present value of capital and interest recoveries, deriving from the collection process, after workout expenses. The recovered cash flows have been discounted at the risk-free rate for the correspondent maturity.

The ratio between these discounted recoveries and the bank's exposure at the moment of default, represents the so called "recovery rate", that is 1 minus LGD.

The New Basel accord provides a precise definition of the event of default, as a point of reference for the estimation of all credit risk components (PD, LGD and EAD). Besides doubtful debts, it is necessary to consider loans which can be temporarily non performing and over 90 days past due loans[7]. These are bad loans which are more likely than doubtful debts to become performing again[8]; so, a measurement which ignores them leads to an LGD overestimation.

The determination of an LGD which is Basel compliant requires to study the evolution of all non accrual loans: in particular, it is necessary to estimate the percentage of loans which get performing again (the so called "cure rate") and the portion of those which get worse, turning to doubtful. These percentages are then used to adjust the LGD which has been measured on the grounds of the worst credits. The examined bank has been working on these data, but at the moment they are not available.

The composition of our sample can be described according to five "analysis axes":
- the collection process's length;
- the geographical areas where borrowers are settled;
- the borrower segments;
- the loan types;
- the kinds of security which has been given to the bank.

The length of the workout process of the loans included in our sample, ranges from a minimum of less than one year, to a maximum of 23 years. The half of the recovery procedures come to an end within two years, and 75% ends up before five years. Processes longer than eleven years are outliers, since they occur only in a few cases.

The upper part of Chart 1 gives us information about the average LGD by collection process's length. A careful observation allows us to notice that as length grows, LGD gets higher, but as length exceeds ten years, LGD becomes steady at around 70%[9]. There seems to be a temporal threshold beyond which the financial cost related to the procedure lenght does not grow any more.
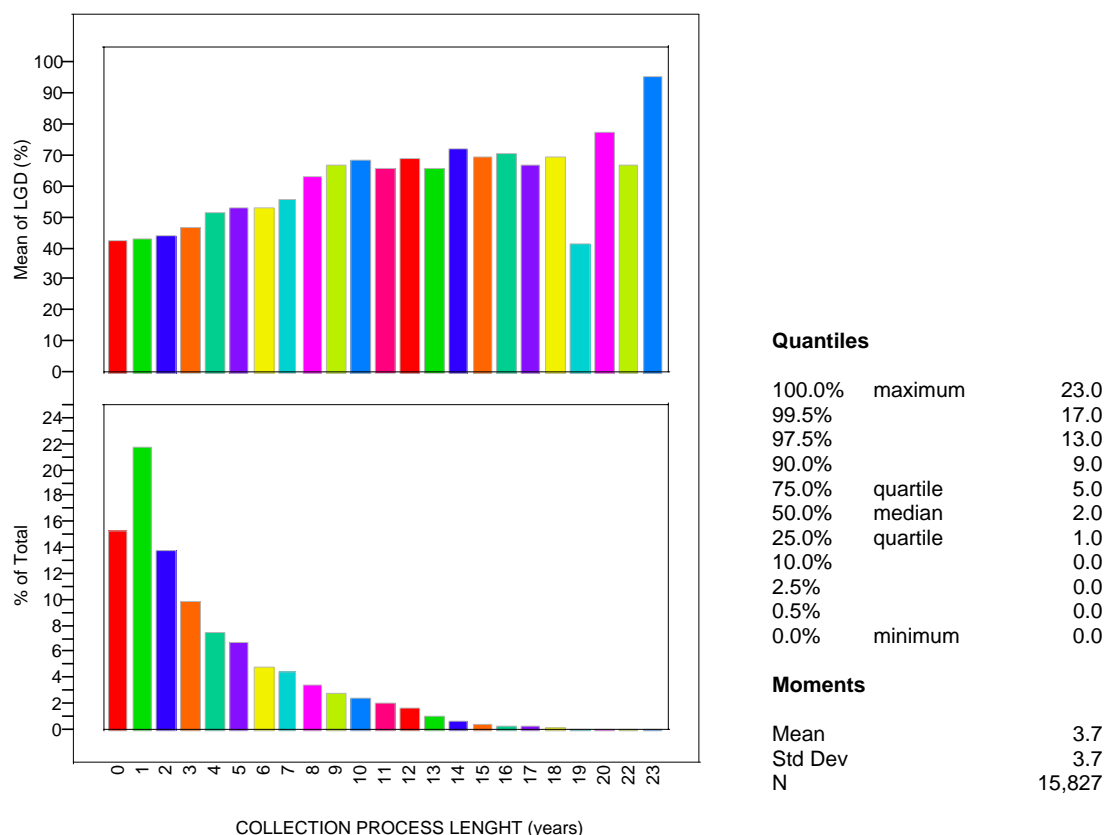
---

[7] Italy has chosen the option which allows to consider over 180 days past due loans.
[8] ABI (2002).
[9] Ignoring procedures lasting more than 18 years.

4

Chart 1 – Average LGD by workout process's lenght

Mean of LGD (%)

% of Total

COLLECTION PROCESS LENGHT (years)

Quantiles

100.0%	maximum	23.0
99.5%		17.0
97.5%		13.0
90.0%		9.0
75.0%	quartile	5.0
50.0%	median	2.0
25.0%	quartile	1.0
10.0%		0.0
2.5%		0.0
0.5%		0.0
0.0%	minimum	0.0

Moments

Mean	3.7
Std Dev	3.7
N	15,827

According to the borrowers' location, we can single out four settlement areas: the North-West of Italy, the North-East, the Centre and the South (see Table 1).
Most borrowers are concentrated in the North-West of Italy (nearly 94% of our sample), while 3% is located in the North-East. The remaining 3% is settled in the Centre (2%) and in the South (1%).
The North-East area is the borrowers' location to which is associated the highest average LGD (62.1%); moreover, on 50% of the defaulted loans related to that area, the bank losses over 85%.
On the contrary, to the North-West area is associated a 49.3% LGD, even if the length of the recovery procedure is higher than the sample mean.

Table 1 – LGD Statistics according to the borrowers' location

BORROWER'S AREA	% of Total	Mean of LGD (%)	Std Dev of LGD (%)	Median of LGD (%)	Average collection process's lenght (years)
C	1.9	49.0	43.0	38.5	3.0
NE	2.9	62.1	41.6	85.5	3.1
NW	93.8	49.3	43.5	45.0	3.8
S	1.3	54.1	41.0	48.5	2.3
Total	*100*	*49.7*	*43.4*	*46.2*	*3.7*

Referring to the borrower category, our sample includes observations about three segments: "retail customers", "small and medium enterprises" (sme) and "very small enterprises". So, the LGD estimation we are going to describe is predominantly referred to small-sized grantees.

In particular, "retail customers" category coincides with that of "consuming households" which is considered in Bank of Italy's studies. Instead, the other segments are identified on the basis of two discriminant parameters: sales and the amount of the credit line.

Sme are businesses whose sales range from 1 to 100 million euros, while very small enterprises are characterized by less than 1 million euros of sales and they are entrusted with less than 250,000 euros[10].

Table 2 shows that the loans included in our sample are equally enough distributed between retail borrowers and corporates (45% and 55%, the latter composed by 16.3% of "sme" loans and 38.4% of "very small enterprises" loans).

Loans to retail customers exhibit a 53.3% LGD on average, but their workout process lasts less than others; on the contrary, small business loans are characterized by the lowest LGD, but at the same time it takes four years or more to collect them.

Table 2 – LGD statistics by Borrower category

BORROWER SEGMENT	% of Total	Mean of LGD (%)	Std Dev of LGD (%)	Median of LGD (%)	Average collection process's lenght (years)
retail	45.3	53.3	45.1	57.4	3.1
sme	16.3	48.4	40.3	46.4	4.5
very small	38.4	46.0	42.3	37.8	4.0
Total	*100*	*49.7*	*43.4*	*46.2*	*3.7*

As to the loan form, over 58 % of the sample is composed by short term loans, while 42% includes medium and long term loans.

Referring to the short term, 49% of the sample is represented by cash flow financing[11], while 9.2% are discounts & advances. On the other hand, medium and long term loans include consumer credit (3%), leasing (1.4%), long term loans to corporates (that support industrial investment, 13%) and long term loans to retail customers (24%, e.g housing loans).

Consumer credit is the type of loan on which, in the event of default, the surveyed bank losses more: the average LGD is 79%, the 25% quartile is 83.75% and the median is 100%. At the same time, the workout process lasts only 2.5 years on average, much less than other loans' recovery procedures: discounts & advances are collected in five years on average, but LGD is "only" 56.6%.

Long-term loans to corporate exhibit the lowest LGD (37.6%), even if it takes nearly four years before they are recovered.

---

[10] Companies whose sales amount for more than 100 million euros are classified as "large corporates", while businesses with less than 1 million euros of sales and entrusted with more than 250,000 euros are also "very small enterprises", but data about both categories are not available at the moment.
[11] Cash flow financing is oriented to cover contingent lack of liquidity in households' and businesses' activity.
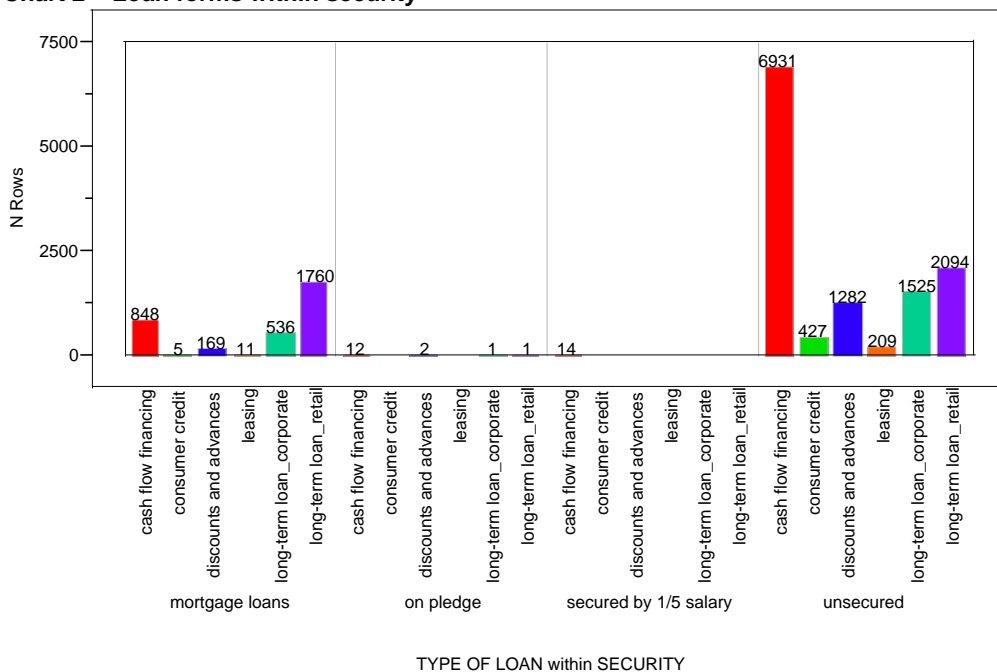
Table 3 – LGD statistics by Loan type

LOAN TYPE	% of Total	Mean of LGD (%)	Std Dev of LGD (%)	Median of LGD (%)	Average collection process's lenght (years)
cash flow financing	49.3	54.7	43.7	61.1	3.7
discounts and advances	9.2	56.6	43.5	72.8	5.0
consumer credit	2.7	79.1	37.9	100.0	2.5
leasing	1.4	48.0	42.1	36.6	2.8
long-term loan corporate	13.0	37.6	37.5	27.1	3.9
long-term loan_retail	24.4	40.3	42.7	19.4	3.3
Total	*100*	*49.7*	*43.4*	*46.2*	*3.7*

Finally, according to the security given to the bank, most of the loans in our sample are unsecured (79%), while 21% are mortgage loans. A minority of debtors have been entrusted on pledge (0.1%), and 0.08% of loans are granted by claim assignment (see Table 4).

Chart 2 shows in details which kind of security has been given to grant each loan form. It is confirmed that most loans are unsecured, and it is also highlighted that mortgage grants above all long term loans, both to corporate and retail borrowers[12].

Chart 2 – Loan forms within security

TYPE OF LOAN within SECURITY

---

[12] Even if cash flow financing is oriented to satisfy short term financial needs, its life actually lasts in the long run.

Higher the bank's lien, lower the loss it suffers from, in the event of default: mortgage loans and loans on pledge are characterized by the lowest LGDs (respectively 24.5% and 31%), in comparison with unsecured loans, even if their recovery procedure is longer.

Table 4 – LGD statistics by Security

SECURITY	% of Total	Mean of LGD (%)	Std Dev of LGD (%)	Median of LGD (%)	Average collection process's lenght (years)
mortgage loans	21.0	24.5	33.1	5.5	4.4
on pledge	0.1	31.0	39.7	9.9	3.7
secured by claim assignment	0.08	41.5	37.1	39.9	2.6
unsecured	78.8	56.4	43.4	66.3	3.5
Total	*100*	*49.7*	*43.4*	*46.2*	*3.7*

3. What drives LGD variation?

The first indicator which provides us information about LGD is the mean; our sample mean is equal to 49.7%, which is quite smaller than the one observed by the Bank of Italy in its most recent survey[13] (62.5%), referred to the whole Italian banking system.
Even if this result appears comforting, considering only the average value is really measleading. More precise information about LGD characteristics comes from the standard deviation (43.4%), which indicates a very wide dispersion of the observed parameter.
In order to explain the LGD variation, we have fitted LGD by six variables: the borrower's area, the borrower segment, the loan form, the security, the length of the workout process (which are the five analysis axes considered before) and the borrower's code (obviously considered as a character, not as a numeric variable).
Table 5 shows the achieved R^2 score, which quantifies the portion of LGD variation, resulting from each X variable.

Table 5 - Fit LGD by other variables (R^2)

BY	Borrowers' area	Borrower segment	Loan type	Security	Borrower's code	Workout process's lenght	ALL VARIABLES but Borrower's code	WHOLE MODEL
LGD	0.3%	0.6%	4.3%	9.0%	91.6%	3.6% (+)	16.7%	92.1%

(+ / -): between numeric variables, sign of the Least Square Regression Model

Considering the above variables separately, almost none of them is able to explain LGD variation: neither loan type, nor security seem to be very influencing (R^2 next to 0%), nor even the length of workout process. Moreover, there seems to be no connection of LGD with borrower's area, nor with borrower segment. These four variables all together explain only 16.7% of LGD dispersion.

---

[13] See Banca d'Italia (2001), *op.cit.*

The only factor which is really explanatory is the borrower himself (here represented through a code): his characteristics, by themselves, explain 91.6% of the LGD variation. The whole model R^2 (multiple regression by five variables) reaches 92%, thanks to the considerable contribution of the borrower's features.

This means that, other things be equal, the characteristics of the defaulted borrower can influence the portion of the credit that the bank is able to recover. In other words, once a certain borrower is insolvent, his peculiarities and his behaviour during the collection process, may have a great influence on ultimate LGD.

Let us make some more investigation, by examining LGD of the following four subsets of data: LGD by borrower's area; LGD by loan type, LGD by borrower category, and LGD by security.

Within each subset, we have applied a "fit Y by X" model, where Y is the subset's LGD and X is, from time to time, the borrowers' area, the borrower segment, the loan form, the security, the collection process length, and the borrower's code. We have finally obtained an R^2 score, which quantifies the portion of variation in the subset's LGD, resulting from the X variable. When the "fit Y by X" model has been applied to variables which are both numeric (i.e. LGD by workout process length), we have indicated the sign of the regression in brackets.

Table 6 - Fit Area_LGD by other variables (R^2)

BY	Loan type	Security	Borrower segment	Borrower's code	Workout process's lenght	ALL VARIABLES but Borrower's code	WHOLE MODEL
Centre_LGD	9.7%	11.7%	4.3%	93.7%	6.5% (+)	29.0%	95.0%
North-East_LGD	4.3%	13.8%	0.2%	87.2%	3.6% (+)	23.0%	89.0%
North-West_LGD	4.2%	8.8%	0.6%	91.7%	3.7% (+)	16.0%	93.0%
South_LGD	3.%	4.7%	5.6%	91.6%	0.1% (-)	11.0%	94.0%

(+ / -): between numeric variables, sign of the Least Square Regression Model

Table 7 - Fit Loan form_LGD by other variables (R^2)

BY	Area	Security	Borrower segment	Borrower's code	Workout process's lenght	ALL VARIABLES but Borrower's code	WHOLE MODEL
Cash flow financing_LGD	0.2%*	3.0%	1.8%	96.2%	2.2% (+)	8.0%	98.0%
Consumer credit_LGD	0.3%*	0.3%*	0.1%*	99.3%	0.0% (-)	0.7%	99.5%
Discounts & advances_LGD	1.1%	0.7%	0.4%	99.0%	11.4% (+)	15.0%	99.2%
Leasing_LGD	0.6%*	2.0%	0.2%	78.0%	10.0% (+)	15.0%	80.4%
Long-term loans to corporates_LGD	0.0%*	0.5%	0.1%	96.0%	10.8% (+)	12.0%	96.0%
Long-term loans to retail_LGD	0.3%*	29.4%	3.0%	99.1%	3.0% (+)	34.0%	99.3%

* : there is not enough variety of areas / level of security / borrower segments in the subset
(+ / -): between numeric variables, sign of the Least Square Regression Model

Table 8 - Fit Borrower segment_LGD by other variables (R^2)

BY	Area	Security	Loan form	Borrower's code	Workout process's lenght	ALL VARIABLES but Borrower's code	WHOLE MODEL
Retail	0.2%*	15.8%	6.6%	96.2%	0.8% (+)	20.0%	97.0%
SME	1.4%*	3.4%	3.4%	85.2%	10.3% (+)	17.3%	85.7%
Very small enterprises	0.3%*	5.0%	4.4%	88.0%	7.5% (+)	15.2%	89.3%

* : there is not enough variety of areas / levels of security / loan forms in the subset
(+ / -): between numeric variables, sign of the Least Square Regression Model

Table 9 - Fit Security_LGD by other variables (R^2)

BY	Area	Borrower segment	Loan form	Borrower's code	Workout process's lenght	ALL VARIABLES but Borrower's code	WHOLE MODEL
Mortgage loans	0.0%*	3.8%	10.7%	93.3%	29.4% (+)	35.0%	94.1%
Unsecured loans	0.3%*	1.6%	3.2%	92.0%	2.6% (+)	7.7%	92.5%

* : there is not enough variety of areas / borrower segments / loan forms in the subset
(+ / -): between numeric variables, sign of the Least Square Regression Model

Information resulting from the above tables, confirms that none of the independent variables is able, by itself, to justify the subset LGD's variation.
A careful observation tells us something more about the relative explanatory ability of X-variables within the different subsets. In particular, security seems to be more influencing with reference to Centre- and North-East LGD, but above all to long-term loans to retail borrowers. Loan form is more explicative of Centre LGD, retail loans and mortgage loans.
Belonging to a particular borrower segment seems to be relatively important in the South area, for long-term loans to retail customers and for mortgage loans.
The length of the workout process is more important to explain LGD referred to the Centre area, to loan forms such as discounts & advances, leasing and long-term corporate loans, to small and very small enterprises, and to mortgage loans. In all these cases, the lenght of the recovery procedure is more important than in other conditions, even if its explanatory power of LGD dispersion is still very low.
The regression of each subset LGD by the variable "length" gives back a positive sign, except with reference to South LGD and to consumer credit LGD; nevertheless, the small number of loans included in these subsets raises doubts about the statistical significance of the results.
Finally, the explanatory ability of the borrower's characteristics is further strengthened, with particular reference to consumer credit, to discount & advances and to long-term retail loans. This means that LGD variation depends not only on the loan type and on security, but also on the characteristics of the borrower to whom the loan is disbursed.

The observation of the LGD distribution, without regard to any particular analysis axis, allows us to highlight two main features:
1. it is bimodal: highest probabilities are actually associated to two different values[14];
2. it is U-shaped, since our LGD distribution tends to have a concentration of observations near the boundaries: indeed, the highest frequencies are associated

---

[14] The same result is achieved by Schuermann (2003), *op.cit.*; Renault, Scaillet (2003), *op.cit.;* Frye (2000) *op.cit.*; Asarnow , Edwards, (1995), *op.cit.*

to the endpoints, 0-10% and 90,1-100%. This configuration is one of the most likely to arise in practice[15].
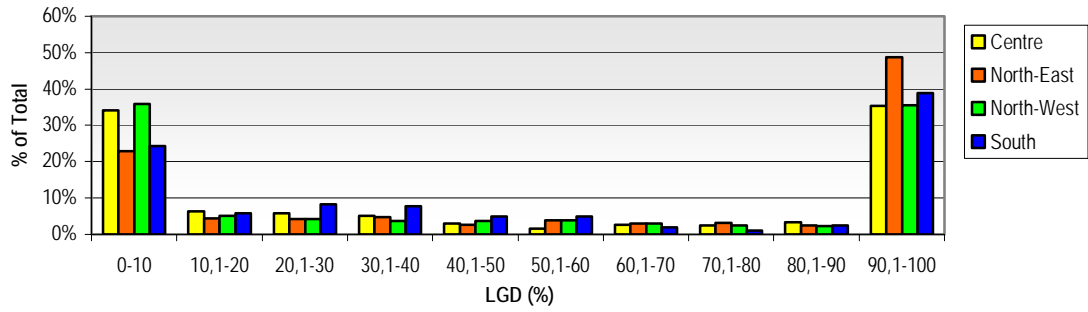
Chart 3 - LGD Distribution
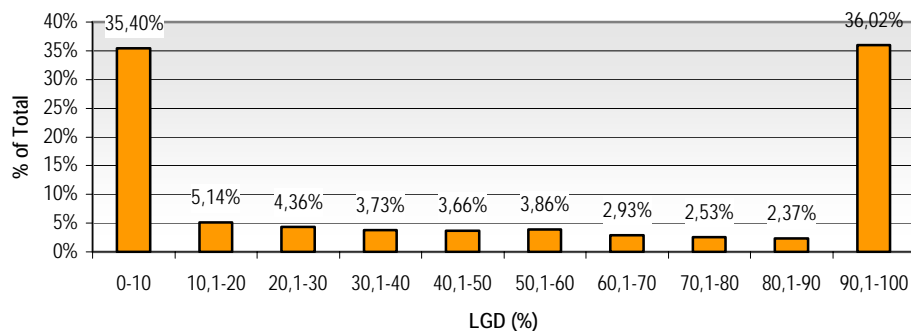
	Quantiles		Moments	
100.0%	maximum	100,00	Mean	49,69
75.0%	quartile	100,00		
50.0%	median	46,22		
25.0%	quartile	1,03	Std Dev	43,41
0.0%	minimum	0,00		

The bimodal shape derives from different characteristics of the statistical units included in the sample; if we studied the height on the basis of a sample composed by men and women, we would observe a bimodal distribution: the highest value is related to the male group, while the second mode is referred to the female one.
The same phenomenon occurs with our sample and it appears to be very accentuated, since the two modes are associated to extreme values.
From the observation of the distribution of our parameter by considering separately each of the above-mentioned analysis axes, it is possible to point out that not all distributions are U-shaped. North-East- and South-distributions are skewed right (Chart 4), as well as those related to consumer credit, cash low financing and discount & advances (Chart 5), to retail loans (Chart 6), and to unsecured loans (Chart 7).
On the contrary, distributions referred to long-term loans to corporate and to retail borrowers and mortgage loans are skewed left.

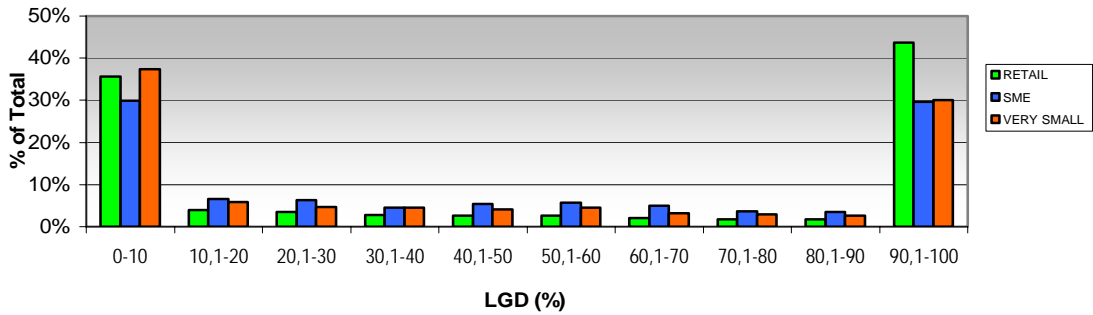[15] For a deeper investigation, see Renault, Scaillet (2003), *op.cit.*

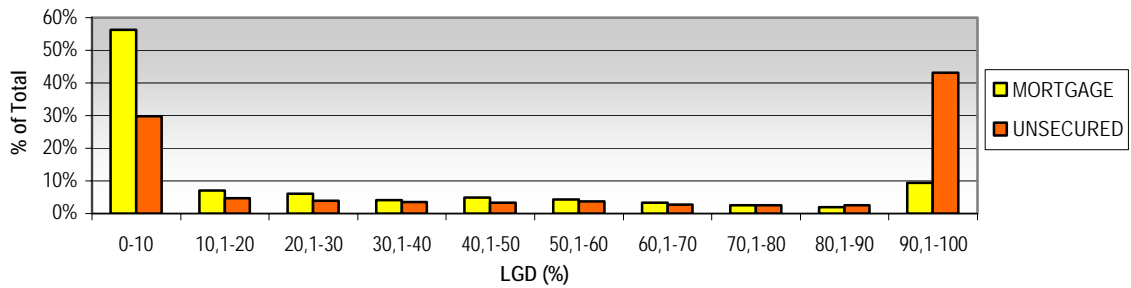**Chart 4 - LGD Distribution by borrowers' settlement area**

Chart 5 - LGD Distribution by loan type
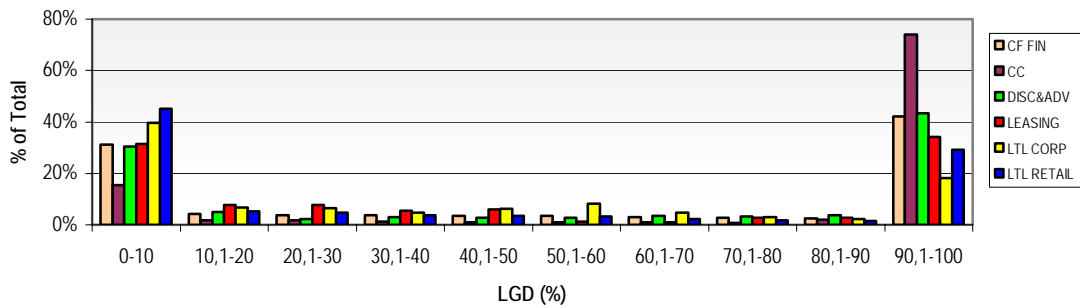
Chart 6 - LGD Distribution by borrower category

Chart 7 - LGD Distribution by security

Conclusions

In this study we have analysed the LGD data on the loans of an Italian commercial medium-sized bank, in order to highlight how it distributes, also according to different aspects: loan forms, borrowers' settlement areas, borrower segments, kinds of security, workout process's length and borrowers' characteristics.

Surprisingly, the length of the collection process does not seem to play a significant role in determining the portion of the distressed loan the bank is able to get back; moreover, there seems to be a year-threshold beyond which the temporal financial cost gets steady.

Really, none of the above-mentioned variables is able to explain LGD if considered separately from the others; moreover, even when we consider the first five variables, LGD is not entirely explained. Only considering also the borrowers' characteristics LGD results really influenced.

The identification of LGD determinants is an essential step in the designing of an LGD rating model, since they contribute to the determination of each rating class. Obviously it is not possible to include single borrowers' features in the designing of the rating classes: it would be the same as having many classes as borrowers are.

Nevertheless, his characteristics could be considered in a next step, for example when LGD rating is applied to price a loan: other things being equal, it could be very different to recover a defaulted loan which was disbursed to a certain borrower, rather than to another one.

References

1. Altman E., Brady B., Resti A., Sironi A. (2003), "The Link between Default and Recovery Rates: Theory, Empirical Evidence and Implications", March, www.stern.nyu.edu.
2. Altman E., Kishore V. (1996), "Almost everything you wanted to know about recoveries on defaulted bonds", *Financial Analysts Journal*, Nov/Dec.
3. Asarnow E., Edwards D. (1995), "Measuring Loss on Defaulted Bank Loans, *The Journal of Commercial Lending*, March, vol. 77, n° 7
4. Associazione Bancaria Italiana (2002), "Loss Given Default - Aspetti metodologici e proposta di una struttura dati per la stima", *I Lavori delle Commissioni Tecniche*, novembre, Bancaria Editrice, Roma.
5. Banca d'Italia (2001), "Questionario recupero crediti: principali risultati", in *Bollettino di Vigilanza*, dicembre, n° 12.
6. Basel Committee on Banking Supervision (2004), *International Convergence of Capital Measurement and Capital Standards, A Revised Framework*, June.
7. Carty L., Hamilton D. (1999), Debt Recoveries for Corporate Bankruptcies, *Moody's Investors Service*, June.
8. Carty L., Hamilton D. et al. (1998), "Bankrupt Bank Loan Recoveries", *Moody's Investors Service*, June.
9. Carty L.V., Lieberman D. (1996), "Defaulted Bank Loan Recoveries", *Moody's Investors Service*, November.
10. Eberhart, A.C. and R.J. Sweeney (1992). "Does the Bond Market Predict Bankruptcy Settlements?", *Journal of Finance,* vol. 47, issue 3.
11. Fridson M. (2000a), "Recovery rates: the search for meaning", Merrill Lynch, March.

12. Fridson M. (2000b), "Recovery trends: any usefulness whatsoever?", Merrill Lynch, August.
13. Frye J. (2000), "Depressing Recoveries", Policy Studies, *Federal Reserve Bank of Chicago*, October.
14. Gupton G., Gates D., Carty L.V. (2000), "Bank Loan Loss Given Default", *Moody's Investors Service*, November.
15. Gupton G., Stein R. (2002), "LossCalcTM: Moody's Model for Predicting Loss Given Default (LGD)", *Moody's Investors Service*, February.
16. Gupton G. (2003), "Advancing Loss Given Default Forecasting Models", Moody'sKMV, www.moodyskmv.com
17. Hamilton et al. (2003), "Default & Recovery Rates of Corporate Bond Issuers. A Statistical Review of Moody's Ratings Performance, 1920-2002", *Moody's Investors Service*, February.
18. Hamilton D., Cantor R. et al. (2002), "Default & Recovery Rates of European Corporate Bond Issuers, 1985-2001", *Moody's Investors Service*, July.
19. Hamilton D., Cantor R., Ou S. (2002); "Default & Recovery Rates of Corporate Bond Issuers", *Moody's Investors Service*, February.
20. Katzengruber B. (2003), Loss Given Default, Ratingagenturen und Basel 2, Österreichische Bankwissenschaftliche Gessellshaft, n° 10.
21. Lazzari V., Laruccia E. (2002), "La misurazione del rischio di un portafoglio crediti con valutazione dell'impato del Nuovo Accordo di Basilea", in *Banca Impresa Società*, n°2.
22. Renault O., Scaillet O. (2003), "On the way to recovery: a nonparametric bias free estimation of recovery densities", *Journal of Banking & Finance*, www.sciencedirect.com
23. Schuermann T. (2003), "What Do We Know About Loss-Given-Default?", *Federal Reserve Bank of New York,* March.
24. Varma P. et al. (2003), "Default & Recovery Rates of European Corporate Bond Issuers 1985-2002", *Moody's Investors Service*, February.