

# The Sensitivity of the Loss Given Default Rate to Systematic Risk: New Empirical Evidence on Bank Loans

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**Abstract** We verify the existence of a relation between loss given default rate (LGDR) and macroeconomic conditions by examining 11,649 bank loans concerning the Italian market. Using both the univariate and multivariate analyses, we pinpoint diverse macroeconomic explanatory variables for LGDR on loans to households and SMEs. For households, LGDR is more sensitive to the default-to-loan ratio, the unemployment rate, and household consumption. For SMEs, LGDR is influenced by the total number of employed people and the GDP growth rate. These findings corroborate the Basel Committee's provision that LGDR quantification process must identify distinct downturn conditions for each supervisory asset class.

**Keywords** Loss given default rate · Bank loans · Systematic risk · New Basel Capital Accord

**JEL Classification Numbers** G21 · G28

## 1 Introduction

Most estimations commonly assume that the loss given default rate (LGDR) is not sensitive to systematic risk. This assumption simplifies the theoretical and mathematical framework on which estimation models are based. However, recent empirical findings (e.g., Frye 2000, 2003, 2005; Altman and Brady 2002; Altman et al. 2002, 2005a, b, c; Acharya et al. 2007;

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Düllmann and Trapp 2004, 2005) have led experts to question the assumption, giving rise to a new research stream.

Although most of the evidence gathered on the sensitivity of the LGDR to systematic risk refers to bonds, the final version of the New Basel Capital Accord (Basel Committee on Banking Supervision 2004a) acknowledges that the evidence for bonds can be generalized to traditional credit exposures. Paragraph 468 states that internal estimates for the LGDR must reflect economic downturn conditions wherever necessary to capture risk accurately. Therefore, for each exposure, the LGDR must not be lower than the average long-term loss rate, weighted for all observed defaults for the type of facility in question. Moreover, banks must account for the possibility that the LGDR may exceed the weighted average value when credit losses are higher than average, thus modeling the so-called “downturn LGDR”.

Although the need to estimate the “downturn LGDR” is clearly framed (see BCBS 2004b, 2005a), Basel II does not provide a specific approach that banks must use in calculating this parameter. Technical and operative details are left to the joint efforts of supervisory bodies and operators in the banking industry (BCBS 2004b, 2005b). Basel II also states that the parameter in question must be gauged during periods when losses on credits are substantially higher than average, although Basel II sets no specific guidelines for identifying the appropriate time frames. In addition, supervisory bodies, along with operators in the banking industry, must decide whether these criteria should be applied to a single portfolio of exposures or to a bank’s entire loan portfolio.

Within this research field, our study has three objectives. The first is to test the hypothesis that there is a relation between the LGDR for bank loans and the state of the economy. The second is to highlight and select the macroeconomic variables so that we can identify periods in which the LGDR should be calibrated; that is, when credit losses are higher than average. The final objective is to provide a way to understand whether determining the LGDR should be applied to a specific class of counterparty or to a bank’s entire loan portfolio.

The nature of the data in this study clearly distinguishes it from other research described in the existing literature, which focuses primarily on LGDRs for corporate bonds. This distinction takes on even greater relevance in light of Basel II, which requires that commercial banks measure credit risk on their traditional lending activities. A second aspect of this study is its broad field of investigation, which goes beyond showing a theoretical relation between LGDR and economic conditions. Lastly, our study is distinguished by our sample, which has a very high number of observations, 11,649 defaulted loans from the Italian market. In addition, information available to us allows us to analyze the LGDR by the customer segment, the type of loan, the type of security, and the business sector of the borrower (where applicable).

Our research highlights that the LGDR on loans to households and the LGDR on loans to small and medium enterprises (SMEs) are statistically different. This evidence is strengthened by univariate regressions, which show that LGDRs for the two customer segments depend on different macroeconomic variables. Therefore, we develop separate multivariate models for the two customer segments and evaluate their goodness either by in-sample or out-of-sample analyses.

The best set of predictors for the LGDR on loans to households comprises the default rate of households, the unemployment rate, and household consumption. For SMEs, the best model considers the GDP growth rate and the aggregate number of employees.

We do not claim that LGDR and macrofactors are linked by a mechanical casual relation. Instead, we identify macroeconomic variables that indicate periods during which

banks should pay particular attention to supervising their loans. Indeed, debtors might have not enough assets to be liquidated by banks in case of default.

We believe that periods that can be associated with higher-than-average losses must not be defined based on standard criteria for all counterparties. Instead, such a definition must be drawn up according to criteria differentiated according to customer category. This factor takes on critical importance if, in a bank's loan portfolio, a segment is found that proves to be riskier than others from the standpoint of LGDR sensibility to even a single macroeconomic variable.

This paper is organized as follows. In Section 1 we summarize the empirical evidence gleaned from past studies. In Section 2 we highlight the research hypotheses, outline the make-up of the sample, identify the variables used in the univariate and multivariate regression models, describe Italian macroeconomic environment and bankruptcy rules, and provide feedback on findings of both the in-sample and out-of-sample analyses. Section 3 concludes.

## 2 Literature review

The Basel Committee's requirements for LGDR estimation are the outcome of research results on the sensitivity of the LGDR to systematic risk. In this section we summarize the findings from these studies.

Altman et al. (2005b), analyzing U.S. bonds, find that the default rate and recovery rate (the complement of the LGDR) may depend on the state of the economic cycle. The authors examine around 1,000 U.S. bonds that defaulted between 1982 and 2001, and measure the recovery rate on the basis of the bonds' market value just after default. The macroeconomic variables taken they use as indicators of the state of the economic cycle are the annual GDP growth rate and the annual change in this rate, an index variable that takes the value of one when GDP growth is less than 1.5% and zero when GDP is greater than 1.5%; the annual return on the S&P 500 stock index, and its annual change. The authors take into account additional variables typical of the bond market, such as the weighted average default rate on high-yield bonds and the natural logarithm of this rate, annual variation in the default rate, and the total amount of high-yield bonds issued every year, or the total amount of high-yield bonds outstanding every year.

Using a univariate regression these authors show that macroeconomic variables do not have the same explanatory power as do variables pertaining explicitly to the bond market. The correlation between the recovery rate and the GDP annual growth rate is very low, as is the case with annual variation in the GDP. Not even the S&P stock index yield is significant in explaining the recovery rate.

What emerges from the Altman et al. (2005b) multivariate regression is that the natural logarithm of the default rate and the annual variation in this rate are extremely significant in calculating the loss rate. Slotting in variables associated with the high-yield bond market improves the model's overall explanatory power by approximately 7%. By contrast, when the authors factor the GDP growth rate and its annual change into the statistical computation, the outcome is not significant, as is the case when they use the yield on the S&P 500 stock index. The results obtained by Altman et al. (2005b) corroborate previous findings in Altman et al. (2005a) and Altman and Brady (2002). The annual growth rate of GDP and annual change in this figure cannot explain the recovery rate. However, these studies do not rule out the possibility that the recovery rate may be sensitive to different economic indicators.

In Frye (2005), the links between the recovery rate, the default rate, and the state of the economy are more concrete. Examining nonfinancial U.S. issuers, Frye analyzes the evolution of the loss rate on 859 bonds and negotiable loans that defaulted from 1983 to 2001. To develop his model, Frye measures the LGDR as the average price of the debt instruments, taken from 2 to 8 weeks after the default event. In addition, over the period in question, the author differentiates between years with numerous cases of default (“high default years,” or “bad years”) and years with few defaults (“low default years,” or “good years”), using 4% as a benchmark value. Frye (2005) compares the average loss rate, calculated on outstanding exposures in high default years, with rates observed during low default years. This comparison is carried out for various exposures: senior secured, senior unsecured, senior subordinated, subordinated and junior subordinated. Frye’s findings show a significant relation between the LGDR and the default rate for all types of loans examined in the study. High default rates mean a greater loss rate, and vice versa. Hence, these findings confirm Frye’s earlier results (2000, 2003).

Examining the provision of guarantees, Frye (2005) concludes that during economically favorable years, such guarantees typically have a low loss rate in cases of default. However, at the same time, the guarantees prove to be more sensitive to trends in the default rate. For guaranteed exposures, the change in the LGDR as the state of the economy changes proves to be more than proportional to the change in the default rate. Consequently, debt instruments that should help to protect the lending institution from default are actually extremely subject to systematic risk.

Acharya et al. (2007) show that recovery in a distressed state of the industry (median annual stock return for the industry firms being less than  $-30\%$ ) is lower than the recovery in a healthy state of the industry by \$0.10 to \$0.15 on the dollar.

Researching the sensitivity of the recovery rate to systematic risk, Düllmann and Trapp (2005) provide two major insights. First, they find a negative correlation between default rates and recovery rates on defaulted bonds from 1982 to 1999. Second, they show that the systematic volatility of recovery rates obliges banks to possess greater economic capital, compared to the amount of capital banks would need if the recovery rate and the state of the economy were independent. These findings confirm the outcome of other empirical testing conducted by Düllmann and Trapp (2004).

Unlike the research described above, Altman et al. (2005c) examine a portfolio of 250 bank loans. They compare risk measurements by applying three different approaches to the recovery rate. Their study takes the recovery rate as a deterministic variable. If the variable is deterministic, then we can assume that the dispersion around the average value of the results is zero. This assumption also characterizes the CreditRisk+™ model for portfolio assessment. They also use a stochastic variable not correlated to the default rate, an approach that is also used by CreditMetrics™ to assess a bank’s portfolio; and as a stochastic variable correlated to the default rate. This last approach has never been used in any credit-risk management model.

Using a simulation model, the authors show that if default rates and recovery rates are significantly and negatively correlated, the first and second approaches tend to underestimate risk. Because economic and financial conditions tend to decline for businesses during an economic downturn, a good rating system should produce a drop in the ratings of financed businesses. If the risk weighting that is associated with capital requirements is linked to the ratings of reliable counterparties, the overall capital requirement to which a bank is subject tends to increase during an economic downturn. Thus, the available credit in the economic system could dissipate precisely when it becomes most vital, which would actually accentuate the fluctuations of the economic cycle.

Therefore, to assess the procyclic effects of a strong inverse relationship between recovery rates and default probability, Altman et al. (2005c) run a simulation based on the evolution of a bank loan portfolio.

First, the authors prove that the effect of procyclicality is driven by upward and downward shifts in credit worthiness, rather than by default rates. Hence, adjustments that banks need to make in loan offerings to adhere to capital requirements primarily respond to variations in the quality of risky activities, and only to a lesser extent to actual credit losses. Second, the simulation suggests that if the LGDR evolved with the default rate, and banks were free to adjust their short-term estimates, the effect of procyclicality would significantly increase, regardless of the regulatory mathematical function used to compute capital requirements. The authors argue that this evidence justifies the Basel Committee's decision to require that banks wishing to adopt the advanced IRB approach must use conservative, "long-term" estimates of the LGDR ("downturn LGDR") rather than short-term revisions. At the same time, we note that if the decision diminishes procyclic effects, it also leads banks to update their risk profiles less frequently, striking a delicate balance between stability and accuracy. These findings confirm the outcome of other empirical testing conducted by Altman et al. 2002.

### 3 Empirical evidence on bank loans

In this section we provide an empirical analysis of loans issued by the five largest Italian banks.

#### 3.1 Research hypotheses

Our analysis tests three hypotheses. Our first hypothesis is that there is a relation between the LGDR on bank loans and the state of the economy. We believe that the empirical results emerging from previous studies can be extended to bank loans, as the Basel Committee suggests. Our study closely follows the same research path mapped out by Altman et al. (2005b), and deals with bank loans rather than bonds.

Our second hypothesis is that it is possible to select macroeconomic variables that explain the LGDR variation more effectively than does GDP. We use a large number of macroeconomic variables in the statistical analysis; beyond GDP, we also consider other factors inherent to aggregate supply and demand. Using a large number of macro factors proves useful in determining the criteria for defining the periods for which banks should calibrate the "downturn LGDR". For now, the Basel Committee has left this issue open.

Our third hypothesis is that the periods for which the "downturn LGDR" should be calibrated must be defined according to different criteria for each customer segment of a bank's loan portfolio. This matter has been left unspecified by the Basel Committee.

#### 3.2 Composition of the sample

Our sample consists of loss rates recorded by the five largest Italian banks on 11,649 loans that defaulted between January 1990 and August 2004. We construct our sample from the historical reference data set used to estimate LGDR by the five largest Italian banks, in accordance with the advanced IRB approach of the New Basel Capital Accord, for supervisory purposes.

Our sample banks are all listed on the Mercato Telematico Azionario (Electronic Equities Market) of the Borsa Italiana, in the Blue Chip market segment, which includes joint stock

companies with the largest capitalization. Our sample is completely representative of the Italian market, since the total assets of our sample banks account for 75.7% of Italy's banking system. All banks in our sample have well-established expertise in both retail and corporate banking. They operate throughout Italy with an extensive network of branches. However, three of them concentrate their lending activity in the north of Italy, while the other two are especially concentrated in the centre and in the south, respectively.

Beyond lending to households, the three banks that operate primarily in the north of Italy specialize in making loans to the industry sector, while those banks that concentrate in the centre and in the south of Italy specialize in supporting agriculture, buildings, commerce, hotels, and restaurants.

Table 1 compares the sample banks in terms of their mean, median, and standard deviations of the LGDR. The table also displays the results of group means comparison, which examines if there are bank-level differences in the LGDRs.

Comparisons of each pair of means show that differences in the average LGDRs among our sample banks are not statistically significant. Hence, even if we gathered data from five distinct banks, we could still consider LGDRs as belonging to a joint data set.

Our sample banks calculate the LGDR as the ratio between the volume of historical losses to the exposure at default.

The volume of historical losses accounts for the outstanding balance at default, the usage given default, the recovery flows, the operating costs of handling the legal case, and the financial costs deriving from the length of proceedings. The usage given default measures the average percentage of use of credit in case of default that would not be utilized under normal circumstances. Estimating this parameter seems quite complex, given that the clauses in every credit covenant make this variable different for each kind of loan. Asarnow and Marker (1995) attempt to estimate this variable based on historic data relative to loans from the US bank Citibank, categorized according to rating class.

The exposure at default is made up of the initial default volume and the subsequent capital charges, deriving from usage given default:

$$LGDR = \frac{\left[ C_{def} + I + \sum C_{chg\_CURR} - \sum (C + I)_{rec\_CURR} + \sum (Exp_{CURR} - Exp_{rec\_CURR}) \right]}{\left( C_{def} + I + \sum C_{chg\_CURR} \right)} \quad (1)$$

where  $C_{def}$  is the initial value of defaulted position,  $I$  is the initial value of default interest,  $C_{chg\_CURR}$  is the current value of capital charges,  $C + I_{rec\_CURR}$  is the current value of

**Table 1** Breakdown of sample by bank comparing the sample banks in terms of mean, median, and standard deviations of the LGDR. Banks 1, 2 and 3 operate primarily in the north of Italy. Bank 4 concentrates its lending activity in the center of Italy and Bank 5 mostly operates in the south. Also reported are the results of group means comparison. We compare the absolute difference between means with the difference that would be statistically significant (least significant difference, LSD). Positive values indicate pairs of means that are significantly different at 5%

LGDR comparison among sample banks											
Bank	<i>N</i>	% of total	Mean LGDR	Median LGDR	SD LGDR	Abs(Dif)-LSD	1	2	3	4	5
1	1,925	16.53	0.50	0.39	0.43	1	-0.154	-0.108	-0.041	-0.005	-0.022
2	2,423	20.80	0.54	0.47	0.41	2	-0.108	-0.056	-0.003	-0.057	-0.071
3	1,814	15.57	0.55	0.63	0.41	3	-0.041	-0.003	-0.115	-0.071	-0.048
4	3,318	28.48	0.58	0.64	0.41	4	-0.005	-0.057	-0.071	-0.012	-0.013
5	2,169	18.62	0.53	0.56	0.43	5	-0.022	-0.071	-0.048	-0.013	-0.069

recovered capital plus interest flows, and  $Exp_{CURR} - Exp_{rec\_CURR}$  is the current value of operating costs on the defaulted position, net of recovered costs.

Expenditures and recovery flows are indexed to the date when default proceedings began, deriving the discount rate from the term structure of the short-term (Euribor) and the medium-long-term swap rate (Eurirs).

### 3.3 Descriptive analysis

When we analyze our sample, we find that the average LGDR is 0.54, the median value is 0.56, and the standard deviation ( $\sigma$ ) is 0.43. The average LGDR in our sample is very high compared to Acharya et al. (2007), who report a loan LGD around \$0.20 on the dollar in means and \$0.10 on the dollar in medians. Our average LGDR is also higher than that reported by Carey and Gordy (2004), which is 23% on bank debt.

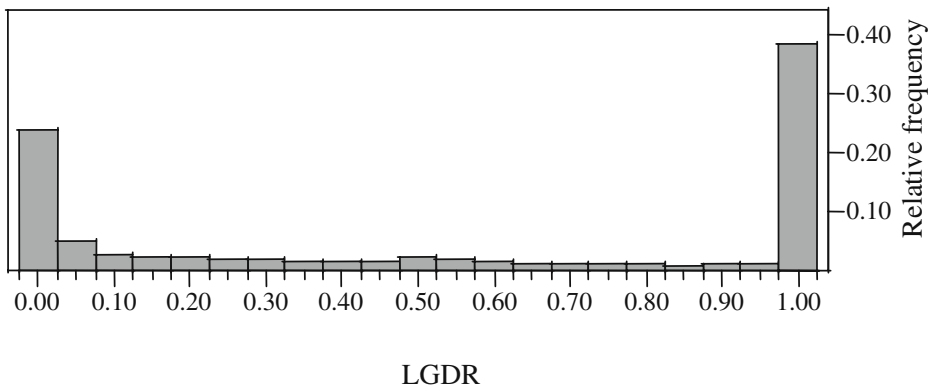
These results depend on the fact that the samples of the said studies are smaller than ours and include bank loans which are granted only to corporates. Moreover, our sample does not include only senior secured bank loans.

Since the standard deviation highlights a considerable dispersion around the mean, the observation of the LGDR distribution in Fig. 1 provides a clearer idea of its features. The figure shows that the LGDR distribution is bimodal. Asarnow and Edwards (1995) and Dermine and Neto de Carvalho (2006) obtain the same result. Extreme values show the highest frequency, and intermediate loss rates occur with a considerably lower frequency.

The category showing a zero LGDR mostly includes loan secured by real estate (about 40% of the subsample). The category that shows a LGDR equal to one primarily comprises cash and advances and special purpose loans to households (about 55% of the subsample).

We can also analyze our sample on the basis of customer segment, type of loan, type of security, and borrower’s field of business.

We identify two customer segments, small- and medium-sized businesses (SMEs) and retail customers. These two segments correspond to those set down for regulatory reasons by the Basel Committee on Banking Supervision (see BCBS 2004a, paragraphs 70, 232 and 273). However, since in our sample the retail segment is made up exclusively of households, we label this segment as “households” in the remainder of this paper. Table 2 shows a balanced distribution between the two segments: 52% of the sample consists of loans to SMEs, and 48% of loans to households.



**Fig. 1** Distribution of loss given default rate. This figure shows the LGDR distribution. The height of each histogram indicates how often each LGDR value occurs

**Table 2** Breakdown of sample by customer segment comparing the customer segments included in the sample, according to their size and in terms of mean, median, and standard deviation of the LGDR. We use *t*-statistic to test for the difference of means between SMEs and households; *t*-statistic=-3.97, which is statistically significant at both 5% and 1%; *p*-value=0.00007121

LGDR comparison between customer segments					
Customers	<i>N</i>	% of total	Mean LGDR	Median LGDR	SD LGDR
SMEs	6,034	51.80	0.52	0.52	0.41
Households	5,615	48.20	0.55	0.68	0.45
Entire sample	11,649	100.0	0.54	0.56	0.43

The average LGDR on loans to households (0.55) is higher than the mean on loans to SMEs (0.52). Student's *t*-test (-3.97) demonstrates that the difference is statistically significant at both 5% and 1%, with a *p*-value close to zero.

However, due to the high variability in the observations, the mean carries little significance. Therefore, examining median values is more useful. An appraisal of these data underscores that in 50% of the cases, the sample banks lose more than 68% on loans to households, compared to 52% on loans to SMEs.

We identify 15 categories of loans. Tables 3 and 4 concerns loans to SMEs, and Tables 5 and 6 reports loans granted to households.

The credits that show the highest average LGDR for SMEs are those labeled as “financial portfolio” (0.68) and “commercial portfolio” (0.65). An even more negative picture emerges when we examine medians: in 50% of the cases, losses on defaults of these kinds of portfolio nearly equal the total amount of exposure. We find that the lowest LGDR on loans to SMEs is for operations secured by a mortgage. It is common knowledge that this type of loan gives banks a greater advantage in satisfying its credit obligations. The average loss rate on “real estate secured current accounts” is 0.23, while the average LGDR on “real estate secured loans to businesses” lies at 0.29. Once again, we find it useful to examine median values, which are less affected by the anomalies found in the sample. On loans guaranteed by a mortgage, the median LGDR is nearly zero.

The group means comparison results (Table 4) show that each subcategory of loans has its own specificity. In terms of the average LGDR, each type of loan proves to be statistically different from most of the other instruments. However, the most significantly different subcategories are “commercial portfolio,” “financial portfolio,” “cash and advances,” and “real estate secured current account.”

For loans to households, the average LGDR on operations labeled as “consumer credit” (0.79) is much higher than the rate for other types of loans. Moreover, the median shows that in 50% of cases, “consumer credit,” “special purpose loans to households,” and “cash and advances to households” typically have an LGDR equal to the total amount of exposure. At the opposite end of the spectrum, we find “real estate secured loans to households,” which, due to the guarantee they provide, have the lowest average LGDR of any category (0.15). In 50% of these cases, the LGDR on these credits is practically nil.

The group means comparison results (Table 6) show that the most significantly different subcategories of loans are “consumer credit,” “unsecured loans to households,” and “real estate secured loans to households.”

In Tables 7, 8, and 9 we examine the behavior of the LGDR across the type of security backing the defaulted loans. Table 7 designates five categories, depending on the type of



**Table 3** Breakdown of the SMEs subsample by loan type comparing the loan categories in terms of the mean, median, and standard deviation of the LGDR. The categories indicated here correspond to transactions reported by Italian banks to the Banca d'Italia (supervisory reports). We define loan types as follows: a “real estate secured current account” is a credit line for which the borrower provides collateral in the form of a mortgage. A “credit commitment” is a promise by the bank to guarantee monetary or nonmonetary obligations taken on by commitment holder toward third parties. The “foreign” category consists of all types of credit granted to back a company’s international transactions. The “real estate secured loans” are self-explanatory. The “other secured loans” are those that provide other types of collateral (cash, stocks, bonds, equipment and commodities). The “commercial portfolio” comprises all unfreezing operations on commercial credit. The “financial portfolio” contains finance bills issued by corporate borrowers. “Special-purpose loans to businesses” are those loans that are earmarked for purchasing specific items that companies need to run their businesses. The “cash and advances” category entails opening a line of credit through a current account

## Loans to SMEs

Loan type	N	%	LGDR		
			Mean	Median	SD
Real estate secured current account	185	1.59	0.23	0.04	0.31
Credit commitments	97	0.83	0.45	0.33	0.41
Foreign	53	0.45	0.59	0.62	0.40
Leasing	220	1.89	0.48	0.37	0.42
Unsecured loans to businesses	144	1.24	0.34	0.18	0.38
Real estate secured loans to businesses	242	2.08	0.29	0.08	0.36
Other secured loans to businesses	216	1.85	0.36	0.21	0.38
Commercial portfolio	673	5.78	0.65	0.94	0.42
Financial portfolio	231	1.98	0.68	0.98	0.41
Special-purpose loans to businesses	830	7.13	0.44	0.47	0.35
Cash and advances	3,143	26.98	0.56	0.62	0.42
Entire sample	11,649	100.0	0.54	0.56	0.43

security: unsecured, other assets, guarantees, Treasury bonds and commodities, and real estate.

About 7.5% of the sample loans are unsecured instruments, which show the highest average LGDR (0.66). On these defaulted loans, the median LGDR even reaches the total amount of the exposure. Other than unsecured loans, the defaulted instruments that show the highest average loss rate are those backed by guarantees, which cover 40% of our sample, and those backed by other assets (equipment and commercial credits). Both categories of loans have an average LGDR of 0.62 and a median which is higher than 0.9.

Among the secured loans, the most common are also those backed by Treasury bonds and commodities (about 31% of the sample), which have an average LGDR of 0.55. However, it is the loans backed by real estate that have the lowest average LGDR (0.18). These loans have a median loss rate that is close to zero, thanks to the security they provide in the event of default.

Table 7 also shows a high standard deviation in LGDR observations, which is common to all categories of loans we explore, except from those which are backed by real estate. The group means comparison proves that average LGDR on loans secured by real estate and Treasury bonds and commodities are statistically different from LGDR on loans backed by other security types. The average LGDR on loans backed by guarantees is not statistically different from the LGDR on loans secured by other assets. Further, the LGDR

**Table 4** Breakdown of the SMEs subsample by loan type reporting the results of group means comparison. We compare the absolute difference between means with the difference that would be statistically significant (least significant difference, LSD). Positive values indicate pairs of means which are significantly different at 5%

Comparison of each pair of means											
Abs(Dif)-LSD	Financial portfolio	Commercial portfolio	Foreign advances	Cash and advances	Leasing commitments	Credit commitments	Special-purpose loans to businesses	Other secured loans to businesses	Unsecured loans to businesses	Real estate secured loans to businesses	Real estate secured current account
Financial portfolio	-0.073	-0.036	-0.030	0.059	0.123	0.136	0.176	0.243	0.251	0.315	0.373
Commercial portfolio	-0.036	-0.043	-0.046	0.056	0.113	0.122	0.171	0.232	0.239	0.305	0.362
Foreign advances	-0.030	-0.046	-0.153	-0.086	-0.013	0.007	0.034	0.107	0.119	0.178	0.239
Cash and advances	0.059	0.056	-0.086	-0.020	0.030	0.037	0.091	0.149	0.155	0.222	0.278
Leasing commitments	0.123	0.113	-0.013	0.030	-0.075	-0.062	-0.022	0.044	0.053	0.117	0.175
Credit commitments	0.136	0.122	0.007	0.037	-0.062	-0.113	-0.081	-0.010	0.000	0.061	0.121
Special-purpose loans to businesses	0.176	0.171	0.034	0.091	-0.022	-0.081	-0.039	0.022	0.029	0.095	0.152
Other secured loans to businesses	0.243	0.232	0.107	0.149	0.044	-0.010	0.022	-0.076	-0.067	-0.003	0.055
Unsecured loans to businesses	0.251	0.239	0.119	0.155	0.053	0.000	0.029	-0.067	-0.093	-0.030	0.029
Real estate secured loans to businesses	0.315	0.305	0.178	0.222	0.117	0.061	0.095	-0.003	-0.030	-0.071	-0.013
Real estate secured current account	0.373	0.362	0.239	0.278	0.175	0.121	0.152	0.055	0.029	-0.013	-0.082

**Table 5** Breakdown of the households sub-sample by loan type comparing the loan categories in terms of the mean, median, and standard deviation of the LGDR. The categories indicated here correspond to transactions reported by Italian banks to the Banca d’Italia (supervisory reports). We define the loan types as follows: the “real estate secured loans” are self-explanatory. “Special-purpose loans to households” are normally taken against the borrower’s wages and are granted to households, again for purchasing specific items (e.g., a personal computer). These operations are not classified as “consumer credit,” which in our study consists of loans that are not “special-purpose loans” and credit cards. The “cash and advances” category entails opening a line of credit through a current account

Loans to households					
Loan type	N	% of the total	LGDR		
			Mean	Median	SD
Consumer credit	432	3.71	0.79	1.00	0.38
Special-purpose loans to households	1,679	14.41	0.65	1.00	0.43
Real estate secured loans to households	1,242	10.66	0.15	0.02	0.24
Unsecured loans to households	71	0.61	0.46	0.43	0.38
Cash and advances	2,191	18.81	0.67	1.00	0.43
Entire sample	11,649	100.0	0.54	0.56	0.43

on loans secured by other assets does not differ significantly from the LGDR on unsecured loans.

When we examine the borrower’s field of business (Table 8), we find that the loans contained in the sample primarily involve the commercial sector and some tertiary sector activities (COMM), such as transportation and communication. Next comes financing for industrial enterprises in the strict sense of the term (IND), other activities generically labeled “other sectors” (OTH), and building (BUILD). The “other sectors” category consists of financial brokerage services, real estate dealings, and other service activities.

**Table 6** Breakdown of the households sub-sample by loan type reporting the results of group means comparison. We compare the absolute difference between means with the difference that would be statistically significant (least significant difference, LSD). Positive values indicate pairs of means which are significantly different at 5%

Comparison of each pair of means					
Abs(Dif)-LSD	Consumer credit	Cash and advances	Special-purpose loans to households	Unsecured loans to households	Real estate secured loans to households
Consumer credit	-0.052	0.081	0.102	0.231	0.601
Cash and advances	0.081	-0.023	-0.003	0.115	0.495
Special-purpose loans to households	0.102	-0.003	-0.026	0.093	0.472
Unsecured loans to households	0.231	0.115	0.093	-0.129	0.221
Real estate secured loans to households	0.601	0.495	0.472	0.221	-0.031

**Table 7** LGDR by security displaying the mean, median, and standard deviation of the loss given default rate as a function of the type of security backing the defaulted loans. Loans secured by “other assets” refer to instruments which are backed by equipment and commercial credits. Also reported are the results of group means comparison. We compare the absolute difference between means with the difference that would be statistically significant (least significant difference, LSD). Positive values indicate pairs of means which are significantly different at 5%

LGDR comparison by security										
Security description/Abs (Dif)-LSD	LGDR statistics					Group means comparison				
	<i>N</i>	Percent of the total	Mean	Median	SD	Unsecured	Other assets	Guarantees	Treasury bonds and commodities	Real estate
Unsecured	878	7.54	0.66	1.00	0.42	-0.038	-0.002	0.010	0.085	0.451
Other assets	823	7.06	0.62	0.90	0.42	-0.002	-0.039	-0.027	0.048	0.414
Guarantees	4,700	40.35	0.62	0.92	0.43	0.010	-0.027	-0.016	0.058	0.422
Treasury bonds and commodities	3,579	30.72	0.55	0.58	0.42	0.085	0.048	0.058	-0.019	0.346
Real estate	1,669	14.33	0.18	0.03	0.27	0.451	0.414	0.422	0.346	-0.027

Financing for agriculture, forestry, and fishing (AGR) are a small portion of the sample in question.<sup>1</sup>

We find the worst average LGDR on loans to those businesses that are included in the “other sectors” category (0.54), although this figure is not very different from that which can be seen for all the other branches of economic activity (0.53 for commerce, transportation, and communication; 0.52 for industry; 0.51 for building sector). Only financing for agriculture, forestry, and fishing show a positive differential, with an average LGDR of 0.45; but given the small number of loans in this category, this result cannot be considered particularly significant. The median LGDRs are similar to the mean values of LGDR. Table 8 also shows a high standard deviation in LGDR observations, which is common to all sectors in the sample.

The group means comparison shows no statistically significant difference among the average LGDRs. This result is confirmed by the univariate regressions, which involve dummy variables, concerning the different business sectors:

$$\text{LGDR} = \alpha + \beta \times D_{\text{OTH}} \quad (2)$$

$$\text{LGDR} = \alpha + \beta \times D_{\text{COMM}} \quad (3)$$

<sup>1</sup> We have reclassified information contained in the data set. For each loan, we have used the code and designation applied by ISTAT (Italy’s Central Statistics Institute), thus ensuring both standard treatment of data as well as a reasonable number of clusters. In this sense, using the RAE code (the Italian acronym for branch of economic activity) would have ensured greater specificity and the creation of subgroups with more internal homogeneity. However, the resulting subgroups would have included too small a number of loans to be considered statistically significant.

**Table 8** LGDR by business sector showing the mean, median, and standard deviation of LGDR. Also reported are the results of group means comparison, with reference to SMEs’ business sectors

LGDR comparison among SMEs’ business sectors										
Business sector/ Abs(Dif)-LSD	LGDR <sub>SMEs</sub> statistics					Group means comparison				
	N	Percent on loans to SMEs	Mean	Median	SD	OTH	COMM	IND	BUILD	AGR
OTH	677	11.22	0.54	0.53	0.42	-0.046	-0.027	-0.024	-0.018	-0.010
COMM	2,743	45.46	0.53	0.53	0.41	-0.027	-0.023	-0.021	-0.017	-0.015
IND	1,878	31.12	0.52	0.52	0.42	-0.024	-0.021	-0.028	-0.023	-0.020
BUILD	646	10.71	0.51	0.50	0.42	-0.018	-0.017	-0.023	-0.047	-0.040
AGR	90	1.49	0.45	0.34	0.42	-0.010	-0.015	-0.020	-0.040	-0.126

$$LGDR = \alpha + \beta \times D_{IND} \tag{4}$$

$$LGDR = \alpha + \beta \times D_{BUILD} \tag{5}$$

$$LGDR = \alpha + \beta \times D_{AGR} \tag{6}$$

In Eqs. 2, 3, 4, 5, and 6,  $D_{OTH}$  is a dummy variable that takes the value of one if industry is “other sectors,” and zero otherwise;  $D_{COMM}$  is a dummy variable that takes the value of one if industry is “commerce, repairs, hotels and restaurants, transportation, communication,” and zero otherwise;  $D_{IND}$  is a dummy variable that takes the value of one if business sector is “industry in a strict sense,” and zero otherwise;  $D_{BUILD}$  is a dummy variable that takes the value of one if business sector is “building,” and zero otherwise;  $D_{AGR}$  is a

**Table 9** LGDR by business sector showing the univariate regressions that involve dummy variables for the different business sectors.  $D_{OTH}$  is a dummy variable that takes the value of one if industry is “other sectors,” and zero otherwise;  $D_{COMM}$  is a dummy variable that takes the value of one if industry is “commerce, repairs, hotels and restaurants, transportation, communication,” and zero otherwise;  $D_{IND}$  is a dummy variable that takes the value of one if business sector is “industry in a strict sense,” and zero otherwise;  $D_{BUILD}$  is a dummy variable that takes the value of one if business sector is “building,” and zero otherwise;  $D_{AGR}$  is a dummy variable that takes the value of one if business sector is “agriculture, forestry, and fishing,” and zero otherwise

Fit LGDR <sub>SMEs</sub> by industry dummies			
Industry dummies	R <sup>2</sup>	t-ratio	p-value
$D_{OTH}$	0.00012	0.85	0.394
$D_{COMM}$	0.000059	0.60	0.550
$D_{IND}$	0.000001	-0.09	0.9270
$D_{BUILD}$	0.00018	-1.05	0.2953
$D_{AGR}$	0.00045	-1.292	0.1981

dummy variable that takes the value of one if business sector is “agriculture, forestry, and fishing,” and zero otherwise.

In Table 9, the  $p$ -values and  $t$ -ratios show that the business sectors’ dummies are not statistically significant at either 1% or 5%. Hence, economic sector is not a discriminating factor of loss rates. Gupton et al. (2000) and Davydenko and Franks (2008) corroborate the results of our analysis.

### 3.4 Variables utilized in univariate and multivariate analyses

The independent variables that we use in this analysis are market variables derived from the Italian banking industry and macroeconomic variables that describe the economic system of our country.

Although the market variables refer to a specific sector of the economy—lending—we believe that they indicate the state of the Italian economy, since banks play a key role in promoting development. The decision to include specific aggregate market variables proves consistent with the analytical path followed by Altman et al. (2005b) in studying the corporate bond market.

We define the following factors as market variables: the yearly change in the default-to-loan ratio ( $\Delta D/L$ ), which we use as our proxy for the nationwide default rate; and the annual amount of bank loans in millions of euros (SF), which we use as our proxy for the aggregate supply of financing.

Among macroeconomic variables, we include indicators inherent to economic growth and aggregate supply and demand. They are the GDP annual growth rate ( $\Delta GDP$ ); the total annual number of employed people (EMP), or annual change in the unemployment rate ( $\Delta UN$ ); the annual household consumption in millions of euros (HC); the total gross annual investments in millions of euros (GI); the total annual production in millions of euros (PROD); and the gross annual available income in millions of euros (GAI).

Our two major sources are ISTAT (Italy’s Central Statistics Institute) and Banca d’Italia (Italian Supervisory Authority on the banking system). ISTAT, specifically the Annual Report (ISTAT, *Annuario Statistico*, from 1990 to 2004), enables us to gather data on macroeconomic variables; we note that data homogeneity is ensured by the fact that variables are expressed in constant prices. Banca d’Italia, specifically the Statistical Bulletin and the Appendix to the Annual Report (Banca d’Italia, *Bollettino Statistico* vol. I, from 1991 to 2005, and Banca d’Italia, *Appendice Statistica alla Relazione Annuale*, from 1991 to 2005), enable us to gather information on the market variables for the entire test period (1990–2004). This source also furnishes in-depth data (e.g., subdivided into households and SMEs) that is especially useful for fulfilling the objectives of our study.

### 3.5 The macroeconomic environment in Italy over 1990–2004

The 1990s began with a slackening of Italian economy, which reflected the negative trend of international trade and the slowdown in consumer and business spending. In 1992 the Italian lira crisis made the situation worse.

At the end of 1993, Italian economy began to recover. The expansion of business investments and exports sustained the economic growth until 1995, but business hiring did not increase much and national consumption was low because of the weak trend of available income.

Due to the slowdown in international trade, in 1996 Italy suffered a downturn in production, which was somewhat improved through government incentives for business

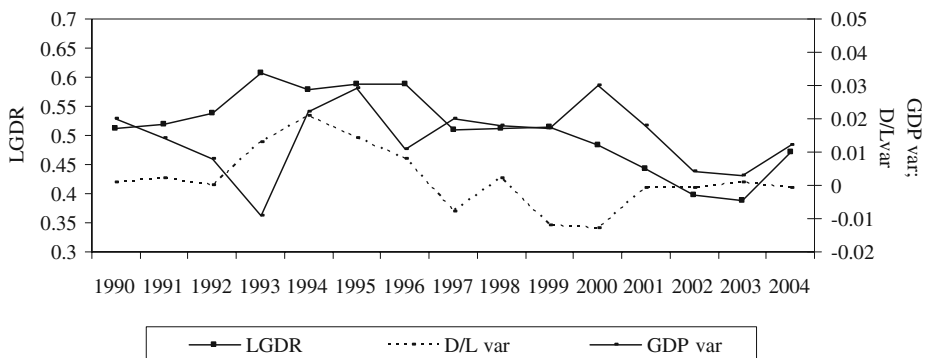
investments. From 1997 to 2001 the Italian economy expanded slightly because of a slackening of exports and consumer spending, which caused a new recession in 2002 and 2003.

The GDP annual growth rate is the most common way to represent whether economy is in expansion or recession and it is usually considered as an input into government economic projections. Another cyclical indicator is the output gap, which is calculated as actual GDP over a given period less potential GDP as a per cent of potential GDP. Potential output refers to the highest level of real GDP that can be sustained over the long term, because of natural, technological, and institutional constraints. It is also referred to as “natural real gross domestic product”. A positive output gap shows that the economy is running hot, while a negative value indicates that the economy is running cold. The output gap plays its largest role in Central Banks’ monetary policy-making process: when an economy is operating at cyclical lows, prices are more likely to drift down, and vice versa; for this reason Central banks usually attempt to keep GDP at or around natural GDP level through monetary policy.

In a strict sense, the economy is in a recessionary phase when the GDP annual growth rate is negative. However, the trend of the other business cycle indicators shows that in Italy, the years from 1992 to 1993, 1996, and the years from 2002 to 2003, identify cyclical lows of the Italian economy.

Figure 2 highlights the time-series behavior of the annual GDP growth rate in 1990–2004. To show how they correlate with the business cycle, Fig. 2 also describes the trend of the nationwide default to loan ratio, which we use as a proxy for the aggregate default rate, and the LGDR.

The years between 1992 and 1996 show a positive variation of the default rate. From 1992 to 1993, the aggregate default rate increased from 5.6% to 6.9%. The 1992–1993 crisis produced a severe effect, so that the aggregate default rate kept on rising through 1994 and 1995, despite the fact that the Italian economy was beginning to recover. In 1996, the aggregate default rate reached its peak at 11.2%. From 1997 on, the annual variation of the default rate was negative or around zero; the  $D/L$  ratio decreased slowly, reaching 8.1% in 2000. The new economic distress in 2002 and 2003 did not affect the aggregate default



**Fig. 2** Italy’s GDP growth rate, annual variation of the aggregate default rate, and LGDR, 1990–2004. This figure shows the Italian GDP growth rate over the period of observation (1990–2004). Years when the GDP growth rate is negative or around zero indicate recession, and vice versa. We use the annual variation of the aggregate default to loan ratio ( $D/L_{var}$ ) as our proxy for the annual variation of the aggregate default rate

rate, which kept steady at 8%. Hence, the GDP growth rate seems not be a good estimator of the annual variation of the aggregate default rate. We test the relation between the latter and macro factors more explicitly in Table 10, in which we analyze loans to households and SMEs separately.

Our regression results confirm that the GDP growth rate is weakly correlated to the annual variation of the default rate, both for households and SMEs ( $R$  is  $-0.179$  and  $-0.221$ , respectively). Other business-cycle indicators prove to be better estimators of  $\Delta D/L$ . For both customer segments, business investments (GI) and household consumption (HC) achieve the best performance and show the highest correlation with the dependent variable, especially for households. Consumer and business spending are an integral part of the aggregate demand and contribute to the growth of households' and businesses' wealth; therefore, we consider these macro factors as indirect indicators of households' and businesses' solvency. The default of both customer segments depends on the same macro factors, because households' bad economic conditions lead inevitable to a worsening in SMEs' earning capacity, and vice versa.

For LGDR, Fig. 2 highlights that annual average loss rate reached its peak in 1993, when the Italian economy suffered from a recession in a strict sense, i.e., a negative GDP growth rate. The observation of the GDP trend in the following years does not show a strong link with LGDR. More findings come from Table 11, which describes the time-series behavior of the historical loss rates, over 1990–2004.

The 1992–1993 crisis severely affected the average LGDR, which increased from 0.52 in 1991 to its peak of 0.61 in 1993. The median value even rose from 0.55 to 0.84.

The short economic recovery in 1994–1995 had only a slight effect on the average LGDR, which stayed around 0.59. The median was more influenced by the economic improvement in 1994, as shown in Table 11. The new economic distress in 1996 did not affect either the average LGDR or the median value. After 1996, both the average and median LGDR showed a steady decrease, despite the new crisis in 2002–2003. The economic slackening probably showed its effects in 2004, when the LGDR increased again.

Table 11 describe the time-series behavior of the different subcategories of loans included in our sample over the period 1990–2004. The average LGDR of different subcategories of loans reflects the overall trend: the 1992–1993 recession caused a strong rise in the loss rate, which continued up to 1996, because the improvement experienced by Italian economic conditions after 1993 was very slight. The categories of loans that showed the highest increase in the LGDR are credit commitments, commercial and financial portfolio, and cash and advances (both to SMEs and to households). We have no data on leasing and “other secured loans to SMEs” for 1992 and 1993; nevertheless, we note that the LGDR in 1994 and 1995 is higher than the mean value for those specific loan types. The economic slowdown in 2002–2003 produced a rise in LGDR only for financial portfolio, unsecured loans (both to SMEs and to households), and cash and advances to households.

Another issue that we wish to note is the decreasing trend of the LGDR on all loans that were secured by mortgages over the period 1990–2004, as shown in Figs. 3 and 4.

Our observation period coincides with a steady increase in the prices of both commercial and residential real estate, which affected the recovery rates on defaulted loans secured by mortgage. Thanks to the considerable rise in real estate prices, the LGDR even became null.

Quantitatively, we find evidence of a negative correlation between the LGDR on real estate secured loans to businesses and commercial real estate prices ( $R=-0.76$ ;  $t$ -ratio= $-3.75$ ;  $p$ -value= $0.0038$ ). We also find evidence that commercial real estate prices influence the LGDR on real estate secured current accounts ( $R=-0.73$ ;  $t$ -ratio= $-3.19$ ;  $p$ -value= $0.0110$ ).



**Table 10** The relation between the variation of the aggregate default rate and macroeconomic factors. This table consists of loans to households and loans to SMEs. Each reads vertically. In the first column, we list the designations of the variables (dependent or independent) used in the analysis, and the designations of indicators that are useful for interpreting the results. We show the values of the autonomous component  $\alpha$ , i.e., the value of the aggregate default rate annual variation when the independent variable is zero, and the coefficient  $\beta$ , which indicates the change that the dependent variable undergoes when there is a unitary variation of the independent variable. We also show the value obtained in the context of Student's  $t$ -test in parentheses; we use this test to assess the significance of the  $\beta$  coefficients (at 5% and at 1%). For each of the  $\beta$  coefficients, we test the  $H_0$  hypothesis ( $\beta=0$ ) as opposed to the alternative hypothesis  $H_1$  ( $\beta\neq 0$ ). If the coefficient differs significantly from zero, (indicated by one or two asterisks next to the value of the coefficient), we can reject the basic hypothesis

Relation between the variation of the aggregate default rate and macroeconomic factors

Loans to households (dependent variable: $\Delta D/L_{\text{HOUSEHOLDS}}$ ; explanatory variables: coefficients and $t$ -ratios)								
Autonomous component	0.036	0.125	1.998	1.015	0.842	0.023	0.387	1.186
$\Delta\text{GDP}$	-2.160 (-0.66)							
$\text{SF}_{\text{HOUSEHOLDS}}$		-9.24e-7* (-2.35)						
EMP			-8.69e-8* (-2.58)					
GI				-5.00e-6** (-5.27)				
PROD					-4.55e-7* (-2.95)			
$\Delta\text{UN}$						0.952 (1.720)		
GAI							-5.27e-7* (-2.23)	
HC								-2.10e-6** (-3.70)
$R$	-0.179	-0.546	-0.582	-0.825	-0.633	0.444	-0.527	-0.717
$R^2$	0.032	0.299	0.339	0.681	0.401	0.197	0.277	0.514
Loans to SMEs (dependent variable: $\Delta D/L_{\text{SMEs}}$ ; explanatory variables: coefficients and $t$ -ratios)								
Autonomous component	0.077	0.169	1.283	0.831	0.661	0.058	0.297	0.888
$\Delta\text{GDP}$	-2.644 (-0.82)							
$\text{SF}_{\text{SMEs}}$		-2.26e-7 (-1.29)						
EMP			-5.43e-8 (-1.42)					
GI				-4.1e-6** (-3.10)				
PROD					-3.38e-7 (-1.95)			
$\Delta\text{UN}$						0.818 (1.45)		
GAI							-3.57e-7 (-1.39)	
HC								-1.5e-6* (-2.19)
$R$	-0.221	-0.336	-0.366	-0.652	-0.475	0.386	-0.359	-0.519
$R^2$	0.049	0.113	0.134	0.426	0.226	0.149	0.129	0.270

\*Significantly different from zero at 5%.

\*\*Significantly different from zero at 1%.

**Table 11** LGDR time-series pattern, 1990–2004. This table shows the mean, median, and standard deviation of the loss given default rate on the entire sample, over our period of observation. It also shows the time-series behavior of the average LGDR, for the different subcategories of loans included in our sample referring to small and medium enterprises and households

Entire Sample				Mean LGDR on loans to SMEs					
Year	Mean LGDR	Median LGDR	SD LGDR	Real estate secured current account	Credit commitments	Leasing	Unsecured loans to businesses	Real estate secured loans to businesses	Other secured loans to businesses
1990	0.51	0.51	0.44	0.18	0.40	1.00	0.29	0.31	no data
1991	0.52	0.55	0.43	0.32	0.48	0.47	0.30	0.54	no data
1992	0.54	0.60	0.44	0.28	0.61	no data	0.34	0.33	no data
1993	0.61	0.84	0.43	0.39	0.62	no data	0.27	0.22	no data
1994	0.58	0.68	0.43	0.19	0.33	0.65	0.45	0.32	0.45
1995	0.59	0.72	0.43	0.24	0.28	0.67	0.24	0.23	0.13
1996	0.59	0.74	0.43	0.15	no data	0.45	0.31	0.30	0.25
1997	0.51	0.49	0.43	0.20	no data	0.31	0.33	0.07	0.09
1998	0.51	0.51	0.41	0.09	0.75	0.58	1.00	0.22	0.18
1999	0.52	0.49	0.38	0.25	0.55	0.46	0.12	0.37	0.56
2000	0.48	0.44	0.43	0.04	0.40	0.45	0.82	0.14	0.05
2001	0.44	0.32	0.41	0.16	0.00	0.42	0.43	0.21	0.42
2002	0.40	0.25	0.40	0.02	no data	0.24	0.54	0.00	0.21
2003	0.39	0.18	0.42	0.00	no data	0.18	0.02	0.00	0.02
2004	0.47	0.33	0.43	0.01	no data	0.55	0.01	no data	no data
Overall	0.54	0.56	0.43	0.23	0.45	0.48	0.34	0.29	0.36

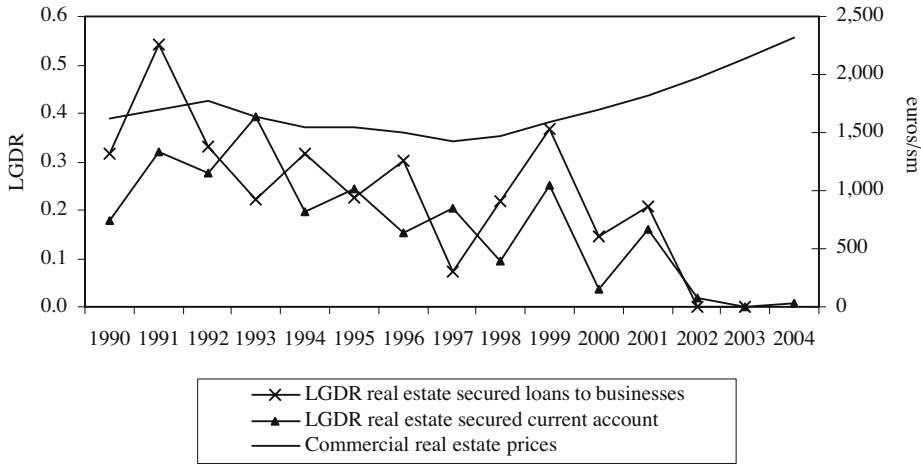
  

Mean LGDR on loans to SMEs					Mean LGDR on loans to households				
Year	Commercial portfolio	Financial portfolio	Special-purpose loans to businesses	Cash and advances to businesses	Consumer credit	Special-purpose loans to households	Real estate secured loans to households	Unsecured loans to households	Cash and advances to households
1990	0.58	0.53	0.44	0.49	no data	0.65	0.24	0.58	0.61
1991	0.62	0.55	0.39	0.53	no data	0.60	0.23	0.63	0.63
1992	0.70	0.67	0.42	0.58	no data	0.57	0.19	0.35	0.66
1993	0.71	0.63	0.48	0.64	no data	0.66	0.24	0.25	0.75
1994	0.72	0.64	0.48	0.65	0.77	0.70	0.17	0.68	0.76
1995	0.70	0.71	0.55	0.59	0.74	0.72	0.15	0.36	0.68
1996	0.71	0.74	0.45	0.61	0.85	0.67	0.12	0.72	0.71
1997	0.57	0.72	0.43	0.57	0.83	0.64	0.08	0.21	0.65
1998	0.63	0.86	0.55	0.58	0.93	0.61	0.12	no data	0.48
1999	0.59	0.69	0.53	0.58	no data	0.52	0.10	0.67	0.80
2000	0.76	0.81	0.51	0.60	1.00	0.67	0.13	0.48	0.64
2001	0.56	0.75	0.40	0.49	no data	0.61	0.07	0.08	0.55
2002	0.33	0.72	0.26	0.46	no data	0.61	0.06	0.58	0.63
2003	0.45	0.62	0.21	0.41	no data	0.56	0.09	0.29	0.64
2004	0.15	no data	0.15	0.49	0.50	0.45	0.03	0.67	0.72
Overall	0.65	0.68	0.44	0.56	0.79	0.65	0.15	0.46	0.67

When we explicitly test the negative correlation between LGDR on real estate secured loans to households and residential real estate prices we find that  $R$  equals  $-0.79$ , the  $t$ -ratio is  $-4.63$ , and the  $p$ -value is  $0.0005$ .

### 3.6 Effect of industry distress

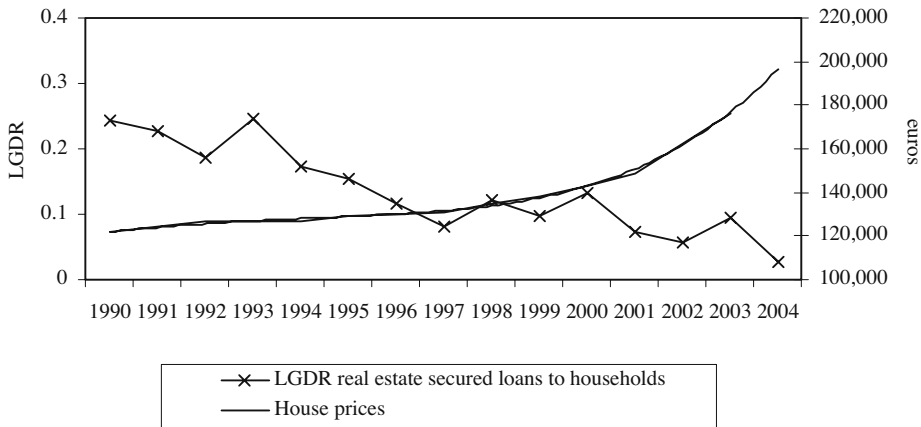
To explore the effect of industry distress on the LGDR, we identify the industries that were distressed over the 1990–2004 period, and the year the distress occurred. We base our identification of distress on data on sectoral production annual growth rate, which we gather



**Fig. 3** The LGDR on real estate secured loans to SMEs and prices of commercial real estate, 1990–2004. This figure compares the trend of the average LGDR on real estate secured loans to SMEs with the trend of commercial real estate prices in Italy, over the period 1990–2004

from ISTAT’s statistical tables over 1990–2004. We classify industries as distressed when the production annual growth rate is less than 1%. Hence, we see that the Agriculture, Forestry and Fishing sectors experienced distress in 1991, 1992, 1993, and 2001; the Commerce, Repairs, Hotels and Restaurants, Transportation, and Communication sectors in 1993; the Building sector in 1993, 1999, 2003 and 2004; Industry in 1992, 1993 and 2003; and Other sectors in 1993 and 1994.

In Table 12 we examine the difference in average LGDRs between no-sectoral-distress years and sectoral distress years, along the lines of Acharya et al. (2007). We use Student’s *t*-test for difference of means. We find that the difference is  $-0.06$  and that it is statistically significant with a *p*-value close to zero.



**Fig. 4** The LGDR on real estate secured loans to households and prices of residential real estate, 1990–2004. This figure compares the trend of the average LGDR on residential mortgages with the trend of house prices in Italy, over the period 1990–2004

**Table 12** Industry distress behavior of LGDR. This table lists the LGDR as the average over the small and medium enterprises sample, the average over the sample whose industry is in distress in a given year, and the average over the remaining SME sample. We classify an industry as being in distress when the sectoral production annual growth rate is less than 1%. The *t*-statistic tests for difference of means, between no industry distress years and industry distress years for the entire SMEs sample and excluding the 1993 defaults

	Mean LGDR	Obs
Entire SMEs sample		
SMEs sample	0.523	6,034
Industry distress years	0.573	893
No industry distress years	0.514	5,141
<i>t</i> -statistic	-3.873**	
<i>p</i> -value	0.00011	
Excluding the 1993 defaults		
SMEs sample excluding 1993	0.516	5,514
Industry distress years	0.541	373
No industry distress years	0.514	5,141
<i>t</i> -statistic	-1.161	
<i>p</i> -value	0.246	

\*Statistically significant at 5%.

\*\*Statistically significant at 1%.

To verify whether our results are driven by just 1 year of economy-wide distress, we test for the difference in average LGDRs between no-industry-distress years and industry distress years, excluding 1993, when LGDR reached its peak. The results of this test are shown in the lower part of Table 12.

We see that the difference in average LGDRs is halved (-0.03), compared with observations that include 1993, and that it is not statistically significant.

This result illustrates that it is not the existence of industry distress per se that boosts LGDR. Instead, it is the existence of an economy-wide recession year that severely affects loss rates on defaulted bank loans. This result contrasts with the findings of Acharya et al. (2007), who document that industry distress is crucial in depressing recoveries.

### 3.7 Italian bankruptcy discipline and resolution of distress

In Italy, insolvency is regulated by two different set of rules, according to the nature of the defaulted debtor: the Bankruptcy Code does not apply to farms, small enterprises (as defined by the Code), or individuals; creditors can take compulsory sale procedures against these categories of debtors.

For the small and medium enterprises included in our sample, our data set does not provide information about the way of distress resolution, so it is difficult to identify the SMEs to which the Bankruptcy Code was applied and those to which it was not. However, a description of Italian bankruptcy discipline can provide useful information that will give us a better understanding of Italy's macroeconomic environment.

Italian bankruptcy procedures were long regulated by the Royal Decree of March 16, 1942, n. 267. Recently, these rules have been substantially reformed by the Law of May 14, 2005, n. 80, and the Legislative Decree of January 9, 2006, n. 5. This reform does not influence our LGDR data, since our sample includes loans that defaulted in the 1990–2004 period, and which were recovered by 2004.

The main bankruptcy procedure was triggered by the insolvency of the entrepreneur, i.e., the impossibility of adequately fulfilling the entrepreneur's obligations. The procedure required that the insolvency status of the entrepreneur was recognized by the Bankruptcy Court. After this recognition, the Court entrusted a receiver with the management of all the entrepreneur's assets, under the supervision of the designated Bankruptcy Judge. After ascertaining the entrepreneur liabilities and acquiring all the assets pertaining to the bankruptcy procedure, including those apparently sold by the entrepreneur and those sold in fraud to the creditors, the receiver proceeded with the liquidation of the assets, after which the receiver distributed the liquidation proceeds among creditors.

To avoid the patrimonial and reputational consequences triggered by the adjudication in bankruptcy, and to partially satisfy the creditors, the entrepreneur could take the preventive creditors' settlement procedure. The entrepreneur had to guarantee that he would be able to pay in full the secured creditors and at least 40% of the unsecured creditors' claims. The entrepreneur maintained the management of his assets under the supervision of a commissioner appointed by the Bankruptcy Court and the direction of the Delegated Judge. The settlement proposal had to be approved by a majority of the creditors and by the Bankruptcy Court. In the event that the settlement proposal was not approved by the creditors or by the Court, the enterprise was subjected to the liquidation bankruptcy procedure.

Another procedure for distress resolution was the compulsory administrative liquidation, which was also aimed at liquidating the defaulted firm. This procedure was provided for banks, insurance companies and cooperatives. In this procedure, after the recognition of the insolvency status by the judicial authority, the administrative authority could cause the termination of activity of the insolvent company and proceed with the liquidation of the assets and the payment of the creditors.

The Bankruptcy Code of 1942 also offered the possibility of reorganizing the enterprise in crisis. The controlled administration procedure provided the entrepreneur with the option to postpone the payment of the debts for up to 2 years at most. Since the entrepreneur was in a situation of temporary financial crisis, he had to demonstrate to the Court that he was capable of re-organizing his enterprise. The use of this procedure had to be approved by most of the entrepreneur's unsecured creditors. If the entrepreneur was admitted into this procedure, then the Court appointed a Judicial Commissioner who supervised the entrepreneur's activity and assisted him in the business management, to the extent necessary.

This examination of the Bankruptcy Act of 1942 points out that the main aim of the bankruptcy procedures was the protection of creditors' interests, pursuant to the principle according to which the insolvent debtor was liable for the fulfilment of the obligations to the extent of all his assets. As a consequence, the main objective was the liquidation of the defaulted firm and its exclusion from the productive system, either in good times or during economic downturns.

This discipline was inadequate from two standpoints. First of all, it showed no consideration for the social and economic effects that the termination of an enterprise might produce, such as negative consequences on employees, negative effects on connected firms, or the risks of contagion in the financial system. Further, these bankruptcy procedures did not bring about a quick and effective liquidation of defaulted firms' assets. In addressing this aspect, Granata (2003) reports that recovery procedures that were discharged between 1988 and 1999, lasted an average of 7 years. Moreover, 45% of those proceedings ended because of shortage of bankruptcy assets. In 49% of cases, discharge of the bankruptcy occurred after liquidation and distribution of assets. Only 6% of the proceedings concluded with payment in full.

Beyond the fact that recovery proceedings were very long, we note that in many cases, bankruptcy procedures were opened when defaulted firms' assets were no longer substantial. Both the length of the liquidation procedures and the lack of bankruptcy assets meant that banks recovered only a very low percentage of their credits. Granata (2003) points out that at the end of the bankruptcy procedures that were discharged between 1988 and 1999, Italian banks were able to recover only 38% of their loans and 23.09% net expenses.

Both law professionals and representatives of the Italian Bankers' Association have requested the Italian legislature to redraft the rules that regulate the bankruptcy procedures.

The Legislative Decree of July 8, 1999, n. 270, regulating the extraordinary administration procedure, provides companies with at least 200 employees with the possibility of being managed by an Extraordinary Commissioner, under the supervision of the Ministry of Industry and Commerce, for a maximum of 5 years. The procedure is aimed at restructuring the enterprise through a reorganization plan. In the event that the plan cannot be completed, the company is closed.

The Law of May 14, 2005, n. 80, and the Legislative Decree of January 9, 2006, n.5, have set new rules that reconcile creditors' and debtors' rights. These new laws strongly safeguard production systems and preserve business continuity. Thus, the new regulations distinguish enterprises that are temporarily in distress from those which are doomed to failure.

The controlled administration procedure has been repealed for those firms that are considered to be only temporarily distressed, since the continuation of interests on debts makes recovery very difficult to achieve. The solution of a temporary crisis is left entirely to the entrepreneur, who is requested to submit a recovery plan to the Bankruptcy Court. If the rescue strategy is unsuccessful, then with the approval of at least 60% of creditors, the entrepreneur can decide to take debt-reorganization agreements, thus avoiding the patrimonial and reputational consequences that would be triggered by the adjudication in bankruptcy and to partially satisfy the creditors.

Thanks to the reform of Italian bankruptcy code, recovery procedures should be more rapid and banks should be able to rescue a higher percentage of their credits. However, as the reform is very recent, there is as yet no evidence about its beneficial effects on the LGDR.

For the insolvent small enterprises and households to which the Bankruptcy Code cannot be applied, recovery of credits takes place through compulsory sale procedures. Banca d'Italia (2001) reports that for procedures that were ended before 1999, forced expropriations of chattels lasted 3 years on average, and that the average length of distraints of real property was 6 years. The length of recovery proceedings undoubtedly influences the legal costs, which are then reflected in a higher loss rate.

For our sample, the length of the recovery proceedings of the defaulted loans ranges from 0 to 14 years. The average length is 3 years; half of the recovery procedures end within 2 years, and 75% end before 4.6 years. Procedures lasting more than 10 years are outliers, since they occur in only a few cases.

We analyze the influence of the procedure length on the LGDR, comparing the average "real LGDR," i.e., indexed to the date of the default event, with the average "nominal LGDR," i.e., measured at the date of emergence from default. The former reflects the impact of the financial costs associated with the length of the recovery proceedings, so it is higher than the nominal loss rate. For this reason, we find that the positive correlation between the real LGDR and the length of the recovery proceedings is almost perfect ( $R=0.986$ ;  $t$ -ratio=21.53;  $p$ -value<0.0001).

Figure 5 depicts the positive difference between real and nominal LGDR. The figure shows what the loss rate would be if the recovery procedure were brief, in comparison with the real value of LGDR, which pays for the financial cost of time.

### 3.8 Analyzing the LGDR and macroeconomic factors

To verify the existence of a link between macro factors and the LGDR, we use a regression model based on the least squares method. We also develop univariate and multivariate analyses. In both types of analysis, we account for two different forms of the specification of the relation between dependent and independent variables, linear and logarithmic. The merit of the latter is that it levels possible peaks in macroeconomic variable trends over time. The following equations sum up the relation between LGDR and the state of the economy:

- Linear form:

$$Y = \alpha + \beta \times X \tag{7}$$

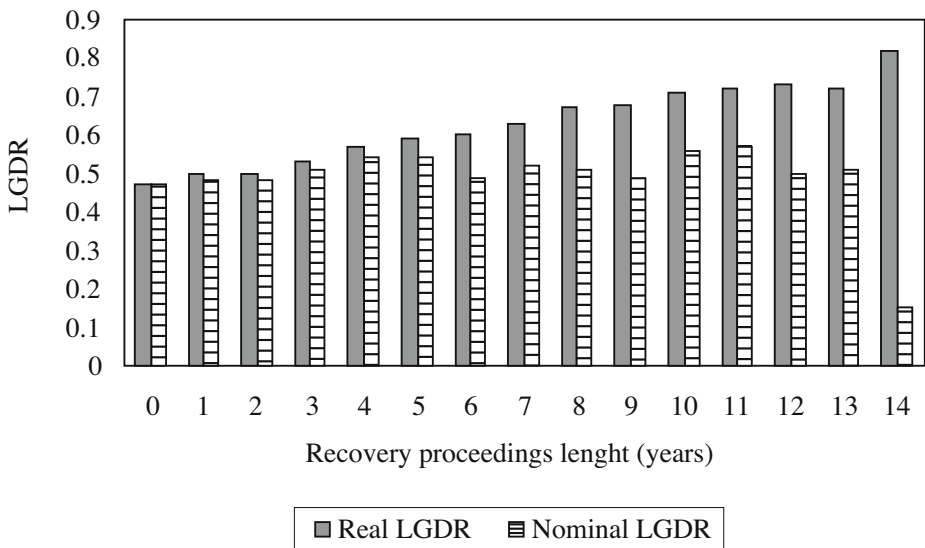
for univariate analysis.

$$Y = \alpha + \beta_1 \times X_1 + \beta_2 \times X_2 + \dots + \beta_k \times X_k \tag{8}$$

for multivariate analysis.

- Logarithmic form:

$$\text{LN}(Y) = \tilde{\alpha} + \tilde{\beta} \times \text{LN}(X) \tag{9}$$



**Fig. 5** The impact of the recovery procedure length on average LGDR. This figure compares the average “real LGDR,” i.e., the LGDR indexed to the date of the default event, with the average “nominal LGDR,” i.e., the LGDR measured at the date of emergence from default

for univariate analysis.

$$\text{LN}(Y) = \tilde{\alpha} + \tilde{\beta}_1 \times \text{LN}(X_1) + \tilde{\beta}_2 \times \text{LN}(X_2) + \dots + \tilde{\beta}_k \times \text{LN}(X_k) \quad (10)$$

for multivariate analysis.

In Eqs. 7, 8, 9, and 10,  $Y$  is the annual average LGDR,  $X$  represents the independent variables used case by case in the univariate analyses, and  $X_i$  indicates the variables included in the multivariate model where  $i=1, \dots, k$ .

When we examine the signs of the correlations, we can plausibly expect a direct relation between the LGDR trend and the variables that reflect an economic downturn as they increase (the annual variation in the default rate and the annual change in the unemployment rate), and an inverse relation between the LGDR and the variables that signal favorable economic conditions as they increase.

### 3.9 The results of the regressions

Tables 13 and 14 show the results of the univariate regression conducted on the 11,649 cases comprising the test sample.

The signs of coefficient  $\beta$  in the regression confirm our previous forecasts. We find a positive sign for the coefficients of the relation between the LGDR and the yearly change in the default/loan ratio, and in the relation between LGDR and the annual variation in the unemployment rate. The coefficients on all other variables are negative. When we examine the intensity of these relations, we should observe the value of the correlation coefficient ( $R$ ) and make a distinction between cases of low and high correlations. To this end, we consider an  $R$ -value of 0.7 (as an absolute value) as a discriminant threshold. (We note that since the  $R$  coefficient ranges from  $-1$  to  $1$ , a value of  $|0.7|$  can be reasonably considered high.)

In Tables 13 and 14 we see a high level of inverse correlation between the LGDR and the variables SF, EMP, GI, PROD, GAI, and HC, under both the linear and the logarithmic relations.

We can also accept the hypothesis of a link between these variables and the LGDR on the basis of the  $t$ -test results (shown in parentheses). All  $\beta$  coefficients referring to the above-mentioned variables differ significantly from zero. Under the logarithmic relation, we see that the LGDR is inversely correlated to real GDP, and directly correlated to the UN.

An analysis of  $R^2$  indicates the extent to which the dependent and independent variables are linked, based on the equation that is applied. Clearly, the greater the value of  $R^2$ , the higher the portion of LGDR variance that is explained by the identified relation.

Keeping the same benchmark used to determine the significance of the correlation coefficient (i.e., a threshold of 0.7), the value of  $R^2$  proves significant only in linear and logarithmic relations between the LGDR and the EMP, and between the LGDR and the GI. At a macroeconomic level, the LGDR is significantly affected by trends in the EMP and the GI.

Contrary to what Altman et al. (2005b), Frye (2005), Düllmann and Trapp (2005) report on defaulted bonds or negotiable loans, and what Altman et al. (2005c) show concerning bank loans, we find no evidence of a strong relation between the aggregate default rate and the LGDR. We achieve a different result when we analyze loans to households and to SMEs separately, as shown at the bottom of Tables 13 and 14. The aim of this in-depth investigation is to test our hypothesis that the LGDRs on the two categories of loans are



**Table 13** Univariate regression on entire sample, and details on SMEs and households. This table should be read vertically. In the first column, we list the designations of the variables (dependent or independent) we use in the analysis and the designations of indicators that are useful for interpreting the results. In the third and fourth lines of the table, the “x” indicates the form that expresses the relation between the variables in question (linear or logarithmic). Below the table, we show the values of the autonomous component  $\alpha$ , i.e., the value of the LGDR when the independent variable is zero, and the coefficient  $\beta$ , which indicates the change that the dependent variable undergoes when there is a unitary variation of the independent variable. We show the value obtained in the context of Student’s *t*-test in parentheses. We use this test to assess the significance of the  $\beta$  coefficients (at 5% and at 1%). For each of the  $\beta$  coefficients, we test the  $H_0$  hypothesis ( $\beta=0$ ) as opposed to the alternative hypothesis  $H_1$  ( $\beta\neq 0$ ). If the coefficient differs significantly from zero (indicated by one or two asterisks next to the value of the coefficient), then we can reject the basic hypothesis. The cells with italicized entries show when the *R*-value is higher than 0.7 (as an absolute value), which indicates a high correlation between LGDR and the independent variable. We also show the adjusted value of  $R^2$ , which we calculate as  $\text{adj}R^2 = 1 - (n - 1/n - k) \times (1 - R^2)$ , where *n* is the number of observations, and *k* is the number of independent variables, including the autonomous component. This index accounts for the number of explanatory variables slotted into the regression to assess its quality

Regression number	1	2	3	4	5	6	7	8	9	10
Dependent variable										
Annual average LGDR	x		x		x		x		x	
LN (annual average LGDR)		x		x		x		x		x
Explanatory variables: coefficients and ( <i>t</i> -ratios)										
Autonomous component	0.499** (33.50)	-0.503 (-1.28)	0.654** (19.54)	3.183** (3.38)	0.525** (31.31)	19.514** (4.16)	2.085** (7.93)	54.538** (6.01)	1.103** (13.89)	13.492** (6.35)
$\Delta(D/L)$	0.327* (2.65)									
LN ( <i>D/L</i> )		0.071 (0.019)								
SF			-2.041e-7** (-4.55)							
LN (SF)				-0.288** (-4.11)						
$\Delta(\text{GDP})$					-1.131* (-2.14)					
LN (GDP)						-1.467** (-4.31)				
EMP							-6.870e-8** (-6.00)			
LN (EMP)								-3.258** (-6.09)		
GI									-0.000003** (-7.50)	
LN (GI)										-1.165** (-6.67)
<i>R</i>	0.59	0.14	-0.79	-0.75	-0.51	-0.77	-0.85	-0.86	-0.90	-0.88
$R^2$	0.35	0.02	0.61	0.56	0.26	0.59	0.73	0.74	0.81	0.77
Adjusted $R^2$	0.30	-0.06	0.58	0.53	0.20	0.56	0.71	0.72	0.80	0.76
Households										
<i>R</i>	0.82	0.24	-0.66	-0.71	-0.46	-0.77	-0.65	-0.65	-0.85	-0.84
$R^2$	0.68	0.06	0.44	0.51	0.21	0.59	0.42	0.42	0.72	0.70
Adj. $R^2$	0.66	-0.02	0.40	0.47	0.15	0.56	0.37	0.37	0.69	0.68
SMEs										
<i>R</i>	0.26	0.08	-0.65	-0.60	-0.44	-0.59	-0.81	-0.81	-0.71	-0.70
$R^2$	0.07	0.006	0.42	0.36	0.19	0.35	0.65	0.65	0.51	0.49
Adj. $R^2$	-0.07	0.001	0.31	0.38	0.30	0.13	0.63	0.62	0.45	0.47

\*Significantly different from zero at 5%.

\*\*Significantly different from zero at 1%.

**Table 14** Univariate regression on entire sample, and details on SMEs and households. This table complements Table 13. In the first column, we list the designations of the variables (dependent or independent) used in the analysis and the designations of indicators that are useful for interpreting the results. In the third and fourth lines of table, the “x” indicates the form that expresses the relationship between the variables in question (linear or logarithmic). Below the table, we show the values of the autonomous component  $\alpha$ , i.e., the value of the LGDR when the independent variable is zero, and the coefficient  $\beta$ , which indicates the change that the dependent variable undergoes when there is a unitary variation of the independent variable. We show the value obtained in the context of Student’s *t*-test in parentheses. We use this test to assess the significance of the  $\beta$  coefficients (at 5% and at 1%). For each of the  $\beta$  coefficients, we test the  $H_0$  hypothesis ( $\beta=0$ ) as opposed to the alternative hypothesis  $H_1$  ( $\beta \neq 0$ ). If the coefficient differs significantly from zero (indicated by one or two asterisks next to the value of the coefficient), we can reject the basic hypothesis. The cells with italicized entries show when the *R*-value is higher than 0.7 (as an absolute value), which indicates a high correlation between LGDR and the independent variable. We also show the adjusted value of  $R^2$ , which we calculate as  $adjR^2 = 1 - (n - 1/n - k) \times (1 - R^2)$ , where *n* is the number of observations, and *k* is the number of independent variables, including the autonomous component. This index accounts for the number of explanatory variables slotted into the regression to assess its quality

Regression number	11	12	13	14	15	16	17	18
<b>Dependent variable</b>								
Annual average LGDR	x		x		x		x	
LN (annual average LGDR)		x		x		x		x
<b>Explanatory variables: coefficients and (<i>t</i>-ratios)</b>								
Autonomous component	1.059** (8.46)	15.170** (4.06)	0.126 (1.21)	1.006* (2.30)	0.785** (10.15)	6.523** (3.05)	1.234** (8.70)	18.723** (4.78)
PROD	-2.982e-7** (-4.40)							
LN (PROD)		-1.099** (-4.24)						
$\Delta$ (UN)			0.548 (1.87)					
LN (UN)				0.752** (3.86)				
GAI					-3.802e-7** (-3.60)			
LN (GAI)						-0.535** (-3.37)		
HC							-0.0000013** (-5.12)	
LN (HC)								-1.464** (-4.95)
<i>R</i>	-0.77	-0.76	0.48	0.73	-0.71	-0.69	-0.82	-0.81
<i>R</i> <sup>2</sup>	0.60	0.58	0.23	0.53	0.50	0.47	0.67	0.65
Adjusted <i>R</i> <sup>2</sup>	0.57	0.55	0.16	0.50	0.46	0.42	0.64	0.63
Households <i>R</i>	-0.77	-0.77	0.52	0.46	-0.65	-0.66	-0.82	-0.83
<i>R</i> <sup>2</sup>	0.59	0.59	0.27	0.21	0.42	0.44	0.67	0.69
Adjusted <i>R</i> <sup>2</sup>	0.57	0.57	0.20	0.15	0.37	0.38	0.65	0.66
SMEs <i>R</i>	-0.58	-0.58	0.28	0.76	-0.60	-0.57	-0.61	-0.61
<i>R</i> <sup>2</sup>	0.34	0.34	0.08	0.58	0.36	0.32	0.37	0.37
Adjusted <i>R</i> <sup>2</sup>	0.29	0.29	0.55	0.004	0.31	0.27	0.32	0.32

\*Significantly different from zero at 5%.

\*\*Significantly different from zero at 1%.

influenced by different explanatory variables. For these regressions, when necessary, we use specific data for each segment. Our findings corroborate the hypothesis that the variables that affect the LGDR value are different for the two customer segments. In particular,  $LGDR_{HOUSEHOLDS}$  is more strongly correlated to annual variation in the  $D/L$ , only under the linear relation; GI, both under the linear and logarithmic relation; PROD, both under the linear and logarithmic relation; HC, both under the linear and logarithmic relation; SF, only under the logarithmic relation; and real GDP, only under the logarithmic relation.

The quality of the regression proves to be higher than or close to 70% only for the annual variation in the  $D/L$  ratio, the GI (both linear and logarithmic) and the HC (both linear and logarithmic).

For SMEs, only EMP and GI are more closely correlated to  $LGDR_{SMEs}$ , under both the linear and the logarithmic relations. UN proves to be a critical variable only under the logarithmic relation. However, the quality of the regression is close to 70% only for the EMP (both linear and logarithmic). We find no relation between  $LGDR_{SMEs}$  and the annual variation of  $D/L$  ratio.

One aspect of our findings emerges as particularly interesting.  $LGDR_{HOUSEHOLDS}$  is more heavily dependent on the annual variation of the default-to-loan ratio at a national level, which also refers to households, than it is for SMEs. The reason lies in the interdependency of two empirical findings. First, as the aggregate default rate rises for households, there is a corresponding increase in the default rates noted for the sample banks. The positive correlation between the two variables is 0.72. Second, in 50% of the cases, each new defaulted loan to households can translate into a loss rate greater than or equal to 0.68 for the sample banks (median value), depending on the specific features of the defaulted loan (security and loan type). This link, in and of itself, contributes to the rise in the annual average value for the  $LGDR_{HOUSEHOLDS}$ .

When we examine loans to SMEs, we find no relation between  $LGDR_{SMEs}$  and the annual variation of  $D/L_{SMEs}$  ( $R=0.17$ ), because the first step in the process described above does not take place. As the aggregate default rate increases for SMEs, there is not necessarily a corresponding rise in the number of defaulted loans to SMEs issued by the sample banks ( $R=0.35$ ). Even if this event were to occur, the effect on the annual average  $LGDR_{SMEs}$  would depend on the impact of each new defaulted loan on the sample banks' overall position. This observation allows us to assert that the phenomenon of procyclicality should have a greater effect on defaulted borrowers who cause the banks to suffer a major loss.

A further note relates to the reason why  $LGDR_{SMEs}$  and  $LGDR_{HOUSEHOLDS}$  are linked to different macroeconomic factors. Our results suggest that the effects of change in macro factors reflect on households and SMEs in a different way.

On the one hand, we have found that a reduction in GI and HC leads to an increase in the annual variation of  $D/L_{HOUSEHOLDS}$ , but we have also found that this event reflects in a rise in the  $LGDR_{HOUSEHOLDS}$ . When aggregate consumption is low indicates that household income is hardly sufficient for living. In this case, it is reasonable to believe that these debtors cannot afford to repay bank loans. Further, a slackening in businesses' investments impacts on their earning capacity and on household income. We suppose that the decrease in households' wealth that leads them to default is also responsible for a lower recovery of credits by banks.

On the other hand, we have found that a reduction in GI and HC leads to an increase in the annual variation of  $D/L_{SMEs}$ , but that this event is not necessarily reflected in a rise in

the  $LGDR_{SMEs}$ . Instead, the regression results suggest that  $LGDR_{SMEs}$  is strongly correlated to GI and EMP. GI influences  $D/L_{SMEs}$  because business investments support the SMEs earning capacity, and thus their solvency. GI is also linked to  $LGDR_{SMEs}$ , because it contributes to the assets that can be liquidated by banks in case of default. Instead, it is not HC, but EMP, that influences  $LGDR_{SMEs}$ . HC supports the SMEs earning capacity, and thus their solvency, while EMP can be considered as an indirect indicator of the equipment, machinery, and physical plant, which banks can sell to recover their credits.

Since we can identify different variables that affect the LGDR for the two customer segments, logic dictates that we must build two separate models for multivariate analysis, one for each segment.

Beyond the previous considerations, the choice of explanatory variables we use in the multivariate regression model is also dictated by an additional factor: the strong correlations among most of the “independent” phenomena. From a statistical standpoint, this occurrence is labeled “multicollinearity,” and it greatly complicates any estimate of the impact of each variable on the dependent variable (in this case, the LGDR).

Each of the two multivariate models of analysis uses independent variables that, based on the outcome of prior univariate testing, have proven to be most strongly correlated to the LGDR. The models also take the multicollinearity phenomenon into account, and as a result, we do not include the variables that show a high intercorrelation ( $R > |0.7|$ ). Therefore, we are able to identify different models and evaluate the explanatory ability of each with respect to both the others and the univariate models described above.

Tables 15 and 16 contain the results of the multivariate analysis for the household and SME segments, respectively. In particular, Table 15 reports the best model specifications, where  $R^2$  is more than 70%.

The analysis of the adjusted  $R^2$  values allows us to ascertain that version 9 of the model is the best model specification. This version involves a logarithmic transformation that shows an adjusted  $R^2$  value of 77%. Versions 8 and 7 give equally good results (adjusted  $R^2$  are 76% and 74%, respectively). These models account for UN, HC,  $D/L_{HOUSEHOLDS}$ , GDP and PROD.

What is obvious is that the GDP has less explanatory power than expected. The best results are captured with a version of the model that does not take GDP into account to explain the average loss rate.

Models 7, 8, and 9 also improve the explanation of LGDR variability with respect to the univariate testing, as emerges when we observe adjusted  $R^2$ . On the contrary, other multivariate specifications do not improve the univariate testing in any way, since only one of the  $\beta$  coefficients differs significantly from zero, either at 1% or 5%.

For the multivariate testing on the LGDR on SME loans in Table 16, version 2 emerges as the best of the various alternatives. In this specific case, the adjusted  $R^2$  value is 66%. Nevertheless, the  $\beta$  coefficient of GDP growth rate differs significantly from zero only at 15%. Therefore, the statistical significance of GDP growth rate is not fully proven.

Except from version 2, all the other applications of the multivariate analysis to  $LGDR_{SMEs}$  prove to be less effective than the results of the univariate analyses, which consider the variables that have the greatest influence on  $LGDR_{SMEs}$ . This result contrasts with what we see in the household segment. It also underscores the fact that the risk of loss in case of default should be monitored especially closely for loans to retail customers, because these loans are more difficult to control. In managerial terms, the value of the loss rate on defaulted loans to SMEs appears to be simpler for intermediaries to monitor, since there are fewer explanatory factors involved. Because of this fact, relevant models need not be particularly complex.

**Table 15** Multivariate regression of LGDDR on loans to households. In this table, the “x” indicates the form that expresses the relation between the variables in question (linear or logarithmic). Below the table, we show the values of the autonomous component  $\alpha$ , i.e., the value of the LGDDR when the independent variable is zero, and the coefficient  $\beta$ , which indicates the change that the dependent variable undergoes when there is a unitary variation of the independent variable. We also show the value obtained in the context of Student’s *t*-test in parentheses. We use this test to assess the significance of the  $\beta$  coefficients (at 5% and at 1%). We also show the adjusted value of  $R^2$ , which we calculate as  $\text{adj}R^2 = 1 - (n - 1/n - k) \times (1 - R^2)$ , where  $n$  is the number of observations, and  $k$  is the number of independent variables, including the autonomous component. This index accounts for the number of explanatory variables slotted into the regression to assess its quality. The table reports the best model specifications, where  $R^2$  is more than 70%

Regression number	1	2	3	4	5	6	7	8	9	10
Dependent variable	x	x	x	x	x	x	x	x	x	x
Annual average										
LGDDR <sub>HOUSEHOLDS</sub>										
LN (annual average										
LGDDR <sub>HOUSEHOLDS</sub> )										
Explanatory variables: coefficients and ( <i>t</i> -ratios)										
Autonomous component	0.556** (17.77)	0.556** (17.77)	1.117* (2.46)	1.125* (2.42)	0.532** (30.05)	0.863** (4.00)	45.185** (5.66)	35.042** (5.99)	37.486** (6.13)	17.589** (5.15)
$\Delta D/L$ <sub>HOUSEHOLDS</sub>	0.443** (3.80)	0.443** (3.27)	0.482** (3.64)	0.446** (3.04)	0.313 (2.07)	0.399* (2.88)	0.595** (3.30)	0.606** (3.48)	0.378* (2.57)	0.072 (0.61)
LN ( <i>D/L</i> ) <sub>HOUSEHOLDS</sub>										
SF <sub>HOUSEHOLDS</sub>										
$\Delta \text{GDP}$	-3.642e-7 (-0.55)	-3.553e-7 (-1.65)	-2.67e- 8 (-1.35)	-0.340 (-0.67)	-1.197 (-2.04)					
LN (GDP)										
EMP										
LN (GI)										
PROD										
LN (PROD)										
$\Delta \text{UN}$										
LN (UN)										
LN (HC)										
$R^2$	0.75	0.75	0.72	0.73	0.80	0.78	0.80	0.81	0.82	0.71
Adjusted $R^2$	0.70	0.69	0.68	0.66	0.74	0.71	0.74	0.76	0.77	0.67

\*Significantly different from zero at 5%.

\*\*Significantly different from zero at 1%.

**Table 16** Multivariate LGDR regression on loans to SMEs. In this table, the “x” indicates the form that expresses the relation between the variables in question (linear or logarithmic). Below the table, we show the values of the independent component  $\alpha$ , i.e., the value of the LGDR when the independent variable is zero, and the coefficient  $\beta$ , which indicates the change that the dependent variable undergoes when there is a unitary variation of the independent variable. We also show the value obtained in the context of Student’s  $t$ -test in parentheses. We use this test to assess the significance of the  $\beta$  coefficients (at 5% and at 1%). We also show the adjusted value of  $R^2$ , which we calculate as  $\text{adj}R^2 = 1 - (n - 1/n - k) \times (1 - R^2)$ , where  $n$  is the number of observations, and  $k$  is the number of independent variables, including the autonomous component. This index accounts for the number of explanatory variables slotted into the regression to assess its quality

Regression number	1	2	3	4	5	6	7
Dependent variable							
Annual average LGDR <sub>SME</sub>	x	x	x	x			
LN (annual average LGDR <sub>SME</sub> )					x	x	x
Explanatory variables: coefficients and ( $t$ -ratios)							
Autonomous component	2.000** (6.08)	1.923** (6.28)	2.053** (5.83)	0.971 (6.03)	1.137* (2.26)	55.850** (4.79)	11.643** (3.30)
$\Delta D/L_{SME}$	0.077 (0.75)		0.016 (0.15)				
LN ( $D/L$ ) <sub>SME</sub>					-0.03 (-0.26)	-0.058 (-0.57)	0.072 (0.60)
$\Delta GDP$	-0.680 (-1.68)	-0.573 (-1.55)		-0.135 (-0.24)			
EMP	-6.46e-8** (-4.51)	-6.14e-8** (-4.58)	-6.74e-8** (-4.41)				
LN (EMP)						-3.348** (-4.84)	
GI				-0.000002* (-2.81)			
LN (GI)							-0.998** (-3.48)
LN (UN)					0.846** (4.09)		
$R^2$	0.72	0.70	0.65	0.51	0.59	0.66	0.50
Adjusted $R^2$	0.64	0.66	0.59	0.43	0.52	0.61	0.42

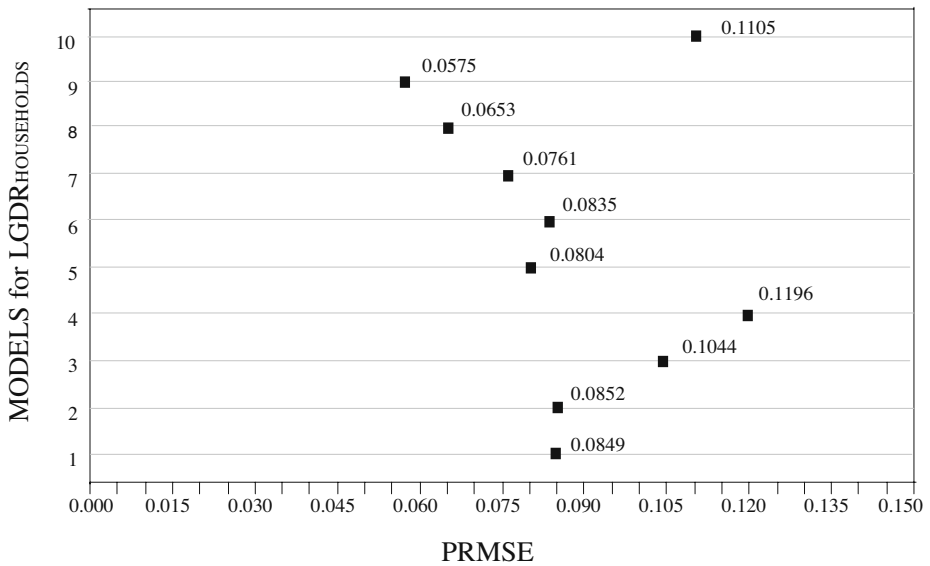
\*\*Significantly different from zero at 1%.

\*Significantly different from zero at 5%.

### 3.10 Out-of-sample analysis of multivariate models

The multivariate analysis carried out so far gives us several estimated models with alternative sets of predictors of LGDR. To identify the best forecast specification for households and SMEs, we conduct an out-of-sample analysis. We refit our multivariate models for 1990–1999 and use them to forecast LGDRs over 2000–2004. Then we select the best forecast model by ranking candidate specifications by their prediction root mean squared error (PRMSE), which we denominate in the same units as the LGDR data, and which measures the distance between forecasted and actual LGDRs over 2000–2004. Hence, the best model specification is the one with the lowest PRMSE.

Figure 6 reports the prediction root mean squared errors of multivariate models for the LGDR<sub>HOUSEHOLDS</sub>. Model 9 proves to be the best forecast model for LGDR on loans to households, achieving the lowest PRMSE among the candidate models (PRMSE=0.0575). The model, which is expressed in logarithmic form, involves the default rate (for



**Fig. 6** Results of out-of-sample analysis on  $LGDR_{HOUSEHOLDS}$ . This figure reports the results of the out-of-sample analysis carried out on our estimated multivariate models for  $LGDR_{HOUSEHOLDS}$ . We refit all models over 1990–1999 and use them to forecast  $LGDR_{HOUSEHOLDS}$  over 2000–2004. We rank the candidate models by their prediction root mean squared error (PRMSE). PRMSE measures the distance between forecasted  $LGDR_{HOUSEHOLDS}$  ( $Y_{Hf}$ ) and actual  $LGDR_{HOUSEHOLDS}$  ( $Y_{Ha}$ ) over 2000–2004. We calculate PRMSE as  $[E(Y_{Hf} - Y_{Ha})^2]^{0.5}$ . The best model specification is the one with the lowest PRMSE

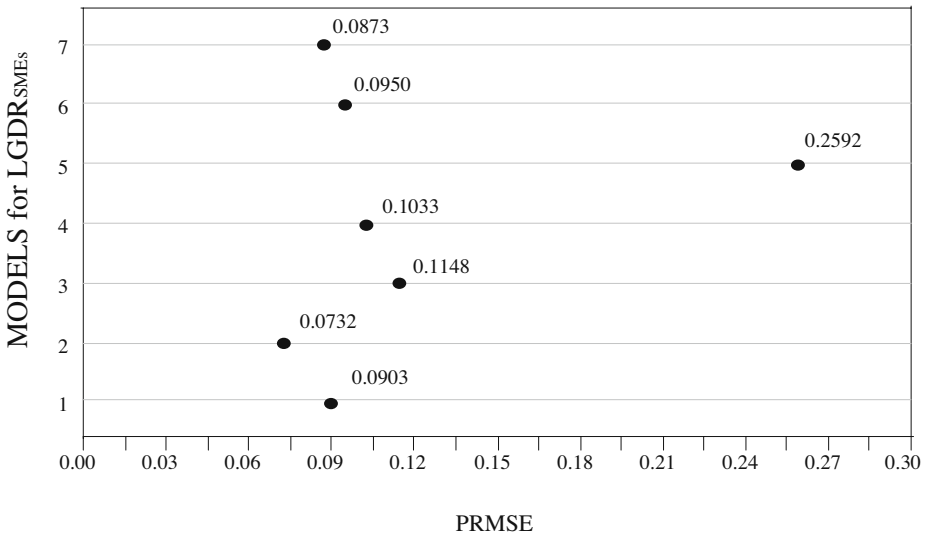
households), the unemployment rate, and household consumption as predictors of the loss rate on defaulted loans to households.  $LGDR$  is positively correlated to  $D/L$  and  $UN$ , but negatively linked to  $HC$ .

Figure 7 reports the results of our out-of-sample analysis on multivariate regressions for  $LGDR_{SMEs}$ . The best forecast model is version 2 (PRMSE=0.0732), which considers the annual GDP growth rate and  $EMP$ . At macroeconomic level, these prove to be the best predictors of  $LGDR$  on loans to small and medium enterprises. The  $LGDR$  is negatively correlated to the GDP annual variation and  $EMP$ .

Our results confirm that  $LGDR_{HOUSEHOLDS}$  and  $LGDR_{SMEs}$  are linked to different macro factors. We consider that this relation is not mechanical. Instead, we believe that this evidence is based on an economic explanation.

For households, we conjecture that periods when aggregate consumption is low indicates that household income is hardly sufficient for living. In this case, it is reasonable to believe that these debtors cannot afford to repay bank loans, and that the value of their properties does not ensure to banks a full recovery of defaulted loans. In the same way, we also consider that the unemployment rate is an indicator of household wealth and income availability, and thus influences recovery rates.

For SMEs, we suppose that slowdowns in the GDP growth rate and in the aggregate number of employees identify periods when SMEs have been downsized. As a consequence, it is reasonable to believe that SME assets are not enough for banks to recover their defaulted credits.



**Fig. 7** Results of out-of-sample analysis on  $LGDR_{SMEs}$ . This figure reports the results of the out-of-sample analysis we perform on our estimated multivariate models for  $LGDR_{SMEs}$ . We refit all models over 1990–1999 and use them to forecast  $LGDR_{SMEs}$  over 2000–2004. We rank the candidate models by their prediction root mean squared error (PRMSE). PRMSE measures the distance between forecasted  $LGDR_{SMEs}$  ( $Y_{Hf}$ ) and actual  $LGDR_{SMEs}$  ( $Y_{Ha}$ ) over 2000–2004. We calculate PRMSE as  $[E(Y_{Hf} - Y_{Ha})^2]^{0.5}$ . The best model specification is the one with the lowest PRMSE

#### 4 Conclusion

Our study, which we conduct on a representative sample of bank loans from the Italian market, shows a relation between the LGDR and macroeconomic conditions. Until now, studies on this topic have proven the existence of such a link solely for corporate bonds, using the GDP as the only macroeconomic explanatory variable.

Our analysis sheds some light on two issues that the Basel Committee has left open for now. Basel II clearly frames the need for banks to estimate the “downturn LGDR”, but it does not present guidelines to define the periods on which LGDR should be calibrated, nor does it specify whether these criteria should be applied to a single portfolio of exposures or to a bank’s entire loan portfolio.

Our empirical research involves a wide range of macroeconomic variables that, in many circumstances, prove to be better explanatory factors than does GDP.

Our univariate analysis highlights that LGDR on loans to households and LGDR on loans to SMEs depend on different macro factors. Thus, we develop separate multivariate models for the two customer segments. Also, multivariate specifications prove the difference between household and SME customer segments for the macroeconomic variables that explain the LGDR value. For households, the best regression model is expressed in logarithmic form and places the LGDR in relation to the default rate (for households), the unemployment rate and household consumption. These variables represent the best set of predictors for  $LGDR_{HOUSEHOLDS}$ , since in the out-of-sample analysis this model achieves the lowest prediction root mean squared error among the candidate specifications.



For the  $LGDR_{SMEs}$ , both the in-sample and the out-of-sample analyses demonstrate that the best model is expressed in linear form and incorporates EMP and the GDP growth rate.

We believe that the difference among the macro factors influencing  $LGDR_{HOUSEHOLDS}$  and  $LGDR_{SMEs}$  is based on an economic explanation.

We suppose that for households, periods when aggregate consumption is low indicates that household income is hardly sufficient for living. In this case, it is reasonable to believe that these debtors cannot afford to repay bank loans and that the value of their properties does not ensure that banks can fully recover on the defaulted loans. In the same way, we consider that the unemployment rate is an indicator of household wealth and income availability. Thus, unemployment also influences recovery rates.

We suppose that for SMEs, slowdowns in the GDP growth rate and in the aggregate number of employees identify periods when SMEs have been downsized. Therefore, it is reasonable to believe that SME assets are not enough for banks to recover their defaulted credits.

Our study demonstrates that an evaluation of the exposure of the LGDR to macroeconomic conditions is more complex for the household segment than it is for the SME segment.

From a risk management standpoint, our findings show that the “downturn LGDR” on loans to households should be calibrated, taking into account the evolution of numerous macroeconomic variables, such as the household default rate, the unemployment rate, and household consumption. For loans to SMEs, the “downturn LGDR” can be calibrated on periods defined according to the evolution of a smaller number of macroeconomic variables, i.e., the aggregate number of employees and the GDP growth rate.

Our study also confirms the need for banks to formulate an internal estimate of the LGDR on loans, that would account for changes in macroeconomic conditions. To effectively determine the “downturn LGDR”, intermediaries must accurately pinpoint macroeconomic factors that actually affect the various loan categories that make up a bank’s portfolio of outstanding credits. Periods that can be associated with higher-than-average losses must not be defined based on standard criteria for all counterparties. Instead, such a definition must be drawn up according to criteria differentiated by customer category. This factor is critically important if, in a bank’s loan portfolio, a segment is found that proves to be riskier than others from the standpoint of LGDR sensibility to even a single macroeconomic variable.

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