EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Benjamin Galow, Oana-Maria Georgescu, Aurea Ponte Marques

Loss-given-default and macroeconomic conditions

No 2954

Abstract

We study the sensitivity of the realised loss-given-default (LGD) to macroeconomic conditions by exploring Global Credit's confidential dataset on observed cash flows from defaulted loans. Given the prolonged duration of loan recovery, spanning several years, and the potential for macroeconomic fluctuations during this time frame, our study explores whether the sensitivity of realised LGD to macroeconomic conditions varies based on the timing of cash flows. We find that, regardless of the cash flow timing, the sensitivity of the LGD to macroeconomic conditions is higher for real-estate secured loans than for unsecured loans. The most relevant macroeconomic variables for the secured LGD are the unemployment rate and stock returns, followed by house price growth and the change in the long-term interest rate. For unsecured loans, real GDP growth and stock returns are the most relevant predictors. These results may be relevant for both micro and macroprudential policymakers by informing on the procyclicality of risk parameters and bank capital requirements.

Keywords: Banks, Financial Risk, Bankruptcy, Business Fluctuations
JEL Codes: G21, G32, G33, E32

Non-technical summary

The focus of this study is the relation between loss given default (LGD) and macroeconomic conditions. The LGD measures the amount financial institutions lose when borrowers default on loans, expressed as a percentage of the total exposure at the time of default. This parameter is an important input for calculating expected credit losses, along with probability of default (PD) and exposure at default (EAD). While the factors influencing PDs are well-studied, there is limited research on the macroeconomic determinants of the LGD, especially in the European context.

The study aims to answer three main research questions. First, does LGD increase during adverse macroeconomic conditions? Second, does the timing of cash flows influence the relationship between LGD and macroeconomic conditions? Third, is the sensitivity of LGD to macroeconomic conditions in the year of default, compared to the year of peak cash flows, more significant for secured loans than for unsecured loans? To test these hypotheses, our study relies on detailed loan cash flow data from The Global Credit Data Consortium (GCD).

The findings confirmed the main hypothesis that LGD tends to increase when the macroeconomic environment deteriorates. However, the second hypothesis was not supported; the timing of cash flows did not significantly impact the sensitivity of LGD to macroeconomic conditions. Notably, we find that, regardless of the timing, secured loans (those backed by real estate) exhibited higher LGD sensitivity to macroeconomic conditions compared to unsecured loans. For secured loans, several macroeconomic variables were significant predictors of LGD, including the unemployment rate, stock returns, house prices, and long-term interest rates. For unsecured loans, only real GDP growth and stock returns were significant predictors. Our results remain qualitatively unchanged when controlling for country characteristics through fixed effects.

Importantly, to the best of our knowledge, this study is the first to use time series of cash flow-based recovery data to analyse the sensitivity of LGD to the macroeconomic environment in the broader European context. Our findings offer valuable insights for both policymakers and financial institutions, aiding in a better understanding of credit risk during varying economic conditions. For instance, these results could provide insights into the procyclicality of bank capital requirements, inform the design of regulatory guidelines for incorporating economic downturn scenarios into LGD models, and support the calibration of countercyclical capital buffers.

1 Introduction

A good understanding of the determinants of banks' expected credit losses is important for both policymakers and financial institutions. Loss given default (LGD) reflects the amount a bank or non-bank financial institution loses when a borrower defaults on a loan, expressed as a percentage of total exposure at the time of default. LGD is one of the key factors used to calculate expected credit losses, alongside with probability of default (PD) and exposure at default (EAD). While the macroeconomic drivers of PDs are well understood, literature on the macroeconomic determinants of the LGD remains scarce, particularly in the European context.

Existing studies on the relation between macroeconomic conditions and LGD yield mixed results. These inconsistencies may be rooted in differences in data granularity, sample size and the econometric method used. Due to the limited availabilty of granular LGD data, only a handful of studies use LGD data derived from actual cash flows collected from defaulted loans. Existing studies using granular cash flow data generally rely on a very small sample size, suggesting that results may be affected by bank or country characteristics. Extrapolating these country level results to the European context may pose challenges due to cross-country differences in the efficiency of the legal framework governing collateral resolution.

Importantly, most studies do not account for the timing of LGD cash flows. The realised LGD of a loan reflects the cash flows collected over the entire period between the time of default and the time of resolution. It remains unclear whether the realised LGD is correlated with macroeconomic conditions at the time of default, at the time of resolution, or somewhere in between.

The timing of cash flows is relevant for two reasons. First, loan restructuring typically lasts several years, during which macroeconomic conditions may change. Second, banks may be reluctant to liquidate collateral assets during economic downturns. This temporal gap between default and loan resolution suggests that the LGD may not necessarily increase during a recession, particularly in the case of secured loans. The regulatory prescribed formula for capital requirements assumes that LGDs reflect economic downturns, neglecting the potential disparity between the macrofinancial cycle and the LGD. This unnecessarily burdens bank capital requirements, potentially impeding macroeconomic recovery after a recession. This aspect is crucial for assessing the procyclicality of regulatory capital requirements. Furthermore, a proper estimation of the relation between LGD and the macroeconomic environment is important for deriving a prudent but plausible estimate of the bank's capital depletion in the context of a stress test.

To capture the timing of cash flows, we consider two distinct points in time at which the macroeconomic variables enter as predictors for the LGD. The first point in time refers to the 'year of default', as typically assumed in regulatory models. The second point in time is the year when the largest fraction of the loan amount is recovered, refereed as the 'year of peak cash flow'.

In this study, we investigate three research questions. First, we hypothesise that the LGD is higher under adverse macroeconomic conditions. Second, we assess whether the timing of cash flows moderates the relation between the LGD and the macroeconomic environment. We expect a lower sensitivity in the year of default compared to the year of peak cash flows, as the latter accounts for the recovery of the largest fraction of the loan amount. Third, we investigate whether the macroeconomic sensitivity of the LGD in the year of default, compared to the year of peak cash flows, is more relevant for secured loans than for unsecured loans. The intuition behind this hypothesis lies in the fact that collateral values constitute the primary channel through which macroeconomic conditions influence LGD.

We relied on granular loan cash flow data from the Global Credit Data Consortium (GCD) to test the above mentioned hypotheses. To account for the bimodal nature of the empirical LGD distribution, we employed a fractional response panel regression with LGD as the dependant variable.

Results confirm our main hypothesis, indicating that LGD increases when macroeconomic conditions deteriorate. However, we did not find evidence for our second hypothesis: the estimations using macroeconomic variables in the 'year of default' versus the 'year of peak cash flow' as predictors yielded similar results. Thus, the timing of cash flows does not significantly affect the sensitivity of the LGD to macroeconomic conditions. Finally, irrespective of the timing, the sensitivity of the LGD to macroeconomic conditions is higher for loans secured by real estate compared to unsecured loans. For secured loans, three out of five macro variables are significant across all specifications. The most relevant macroeconomic variables for secured LGD include the unemployment rate and stock returns, followed by house prices and long-term interest rates. Specifically, the unemployment rate and long-term interest rate are positively related with the LGD, while stock returns and house price growth display a negative relationship. For unsecured loans, only two out of five macroeconomic variables are significant, with a negative relation observed for real GDP growth and stock returns.

While the relation between secured LGD and macroeconomic conditions is driven by the collateral value, the underlying mechanism for the unsecured LGD is less evident. The driver for the latter could be country characteristics, such as the efficiency of the resolution framework. This interpretation is corroborated by empirical evidence showing that resolution times tend to increase during downturn periods. Our results remain qualitatively unchanged when controlling for country characteristics through fixed effects, indicating that the relation between the unsecured LGD and macroeconomic conditions operates through channels other than the legal framework. This is intuitive: firms are less profitable during recessions, leading to a decrease in available income for debt repayment and an increase in the LGD.

To the best of our knowledge, this is the first paper using time series data on cash flow-based recovery to study the sensitivity of the LGD to the macroeconomic environment within the broader European context.

The findings of our paper may be informative for both policymakers and financial institutions. From a micro-prudential perspective, understanding the relation between credit losses and the macroeconomic environment is important for a prudent estimation of risk parameters, ensuring an adequate capitalisation of banks. For instance, our results may offer insights relevant to supervisory guidelines regarding the incorporation of the economic downturn component in LGD models. From a financial stability perspective, our results inform on the procyclicality of bank capital requirements. Finally, the accurate estimation of potential credit losses by banks ensures an efficient loan pricing and, consequently, an efficient allocation of capital requirements across different portfolios.

The paper is structured as follows. The next section provides the literature review. Section 3 presents the data used in this paper. Section 4 describes our empirical strategy. Section 5 summarises the results, while Section 6 validates the empirical strategy. Section 7 concludes.

2 Related Literature

The relevance of macroeconomic variables in predicting credit losses in general, and LGD in particular, is motivated by the relation between macroeconomic conditions and the available income for indebted households and firms: when GDP growth is low and unemployment is high, available income may not be sufficient to repay outstanding debt (see Bellotti and Crook (2012) for a similar reasoning).

Most empirical studies analysing LGD determinants focus on loan and borrower-specific variables. In general, these studies find that smaller loans, higher collateralisation and higher credit quality are negatively related to LGD (Bastos (2010), Dermine and Carvalho (2006)). However, studies analysing the relation between LGD and macroeconomic conditions report mixed results. Bruche and González-Aguado (2010) fit a beta distribution to observed corporate bond recovery rates and find a positive relation between LGD and the credit cycle, but not between the LGD and GDP. A related study using the default database of a large Portuguese bank find no systematic relation between the LGD and GDP growth over a five-year horizon, (Dermine and Carvalho (2006)). Using a large dataset on realised LGD of large European corporations, Brumma and Winckle (2017) observe an inconsistent relation between LGD and GDP growth rate. This study does not distinguish between secured and unsecured loans or cross-country heterogeneity in macroeconomic conditions. Similarly, Grünert (2009) find no relation between LGD and macroeconomic conditions based on a sample of defaulted loans from a large German bank, while Caselli et al. (2008) find a negative association between GDP growth and LGD for five large Italian banks over the period between 1990 to 2004.

Different conclusions on the relation between LGD and the macroeconomic cycle emerge when the level and type of collateralisation is considered. Bellotti and Crook (2012) find a positive relation between unsecured LGD, bank interest rates, and unemployment. Similarly, Konecny et al. (2017) use LGD data from a large Czech bank and find a negative relation between credit growth, GDP, consumption, wage growth, and LGD for consumer credit.

In turn, several studies suggest that the current loan-to-value ratio is the single most important predictor of realised LGD for real-estate secured loans, in addition to the house price index (Qi and Yang (2007); Calem and LaCour-Little (2004); Lekkas et al. (1993); Ingermann et al. (2016)). Ingermann et al. (2016) analyse the determinants of the sales ratio for a portfolio of German real-estate loans and find a significant positive impact of the property condition and location. The source of the property valuation report also played an important role, with reports issued by the court in charge of the foreclosure resulting in a lower sales ratio compared to reports issued by banks. Macroeconomic variables had a counterintuitive coefficient sign: higher GDP growth was associated with a decrease in the recovery rate, while unemployment was associated with an increase in the recovery rate.

The particular shape of the LGD distribution leads to substantial heterogeneity of estimation methods across studies. These range from simple OLS regressions (Qi and Zhao (2011)) to log-log regressions, fractional response, quantile regressions, and regression trees. Dermine and Carvalho (2006)) and Bastos (2010) try to capture the bimodal shape of the recovery rate by using fractional response regressions, while Gupton and Stein (2005) assume a beta distribution for the LGD.

Most of these studies have a small sample size, concentrating on one country or one bank (Dermine and Carvalho (2006), Bellotti and Crook (2012), Ingermann et al. (2016), Konecny et al. (2017)). Cross-country studies spanning a large pool of borrowers over the business cycle are more informative with respect to the relation between macroeconomic conditions, the business cycle and LGD. The most closely related paper to ours is Krüger and Rösch (2017). Similar to the current study, Krüger and Rösch (2017) rely on Global Credit Data on US loans to estimate a quantile regression on the relation between LGD and macroeconomic conditions. While their study finds a significant negative impact of the S&P 500 and the term spread, extrapolating these results to EU countries may be problematic due to cross-country differences in the legal framework governing the resolution process. For instance, US insolvency procedures strongly favour the debtor, whereas in Canada and Great Britain secured creditors have more bargaining power (Betz et al. (2020). These differences impact resolution time and implicitly the timing of cash flows, a key aspect of our estimation.

Therefore, the focus of this paper at is the relation between LGD and macroeconomic variables for defaulted loans in Europe. Importantly, we assign macro variables to LGD both at the time of default and at the time of peak cash flows to capture the variation in the timing of cash flow resulting from cross-country differences in the legal insolvency procedures. If the loan market is distressed at the time of default, the discounted value of ultimate recoveries may be higher compared to the discounted value of recovery values at the time of default (Altman (2006)). Knowing this, banks will wait for better times before liquidating the collateral of defaulted loans, weakening the relation between LGD at the time of default and the macroeconomic environment. Regulators often fail to make the distinction between these two different time frames for calculating the LGD. This distinction is relevant because it raises an important question about the procyclicality of LGD and of bank's capital requirements.

3 Data

Our analysis relies on a unique and confidential dataset of defaulted loans and its observed recovery cash flows from the GCD[1] database. GCD's LGD dataset comprises over 300,000 non-retail defaulted loan facilities from around the world, encompassing over 150,000 borrowers and 11 Basel asset classes. Compiled since 2004, the dataset includes the resolution of defaults from 2000 to today. The long sample period spans several business cycles, including the 2008 global financial crisis and the 2001-2002 dot-com bubble.

Table 1: Sample composition

Loan type	No. Loans	No. of borrowers	No. of banks	No. of countries
Unsecured	7,040	3,552	41	40
Secured	1,672	883	29	30

Notes: This table reports the sample composition, providing the number of loans, borrowers, banks, and countries represented in the dataset, with a breakdown by secured and unsecured loan type.

The sample is restricted to large corporate borrowers reported by 47 European banks in the period between 2000 and 2019. Our analysis excludes loan defaults from 2020 and 2021, reflecting the pandemic-related fiscal and monetary policy measures that weakened the relation between the sudden deterioration in macroeconomic conditions and credit risk variables, such as PD or LGD.

Table 1 presents the composition of our sample by loan type. To analyse the impact of real estate collateral on LGDs, we conducted separate analysis for secured and unsecured loans. Secured loans are collateralised by real estate, while unsecured loans are not collateralised by real estate. Our sample includes 8,712 loans, with 80% being unsecured and the remaining 20% secured by real estate collateral. Table 2 reports the key characteristics of the loans in our sample. The average LGD is lower for secured loans compared to the unsecured loans (18% versus 25%, respectively). The median LGD in the sample is 4% for

[1]The Global Credit Data Consortium (GCD) was formed in 2004 as a credit data pooling initiative primarily designed to assist member banks' completion of Basel II preparations. Member banks exchange default data directly from their books to develop and validate credit data and models.

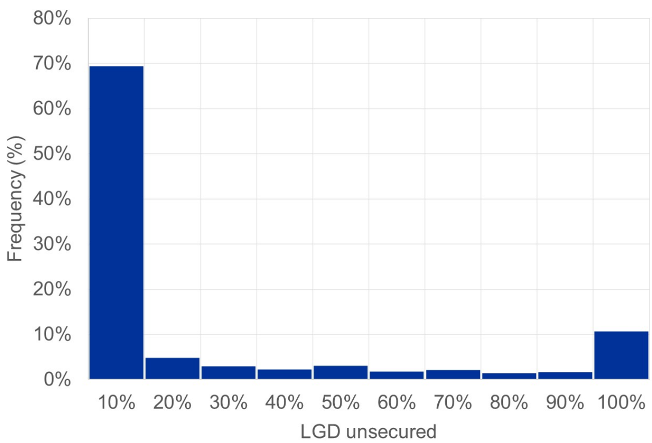
unsecured loans and 2% for secured loans. Figure 1 presents the distribution of LGD in our sample. The distribution exhibits a pronounced bimodal pattern, with two distinct clusters around 0 and 1.

Table 2: Loan characteristics

Loan type	Variable	Q25	Median	Q75	Mean	StdDev
Unsecured	LGD	0%	4%	44%	25%	36%
	EAD	150,676	757,144	3,786,600	8,548,472	46,906,245
	Time to resolution	0.8	1.7	3.4	2.4	2.1
	Time to recovery	0.4	0.8	1.7	1.3	1.3
Secured	LGD	0%	2%	25%	18%	30%
	EAD	310,592	1,138,502	4,772,267	6,809,766	23,529,036
	Time to resolution	0.7	1.7	3.2	2.4	2.3
	Time to recovery	0.4	0.9	1.9	1.4	1.4
	Value of RE collateral	703,375	2,050,000	5,720,218	11,176,726	40,685,255
	LTV	13%	42%	94%	54%	48%

Notes: This table reports the loss-given-default (LGD), EAD (exposure at default), time to resolution (time between loan default and resolution), time to recovery (time between default and peak-cash flow), value of real estate collateral and the loan-to-value ratio for secured loans.

Figure 1: Distribution of LGD unsecured



Notes: The chart shows the distribution of the LGD rate observed across the 7.040 loans in the sample.

Table 3 shows the composition of our sample by industry. The most relevant industries represented are real estate (17% of loans), manufacturing (13%), transportation (10%), and wholesale (10%). A large portion of loans in the real estate sector are secured by real estate collateral (37%). The real estate industry, by its nature, is more closely tied to physical property assets, which can serve as collateral for loans. In contrast, the share of real estate secured loans is significantly lower in other industries, ranging from 1.8% in the agriculture sector to 12.6% in the utilities sector.

As indicated in the introduction, we consider two distinct points in time for which the macroeconomic

Table 3: Sample composition by industry

Loan type	**Unsecured loans**		**Secured loans**	
Industry	**Exposure**	**Cure rate**	**Exposure**	**Cure rate**
Agriculture	0%	19%	1.8%	0%
Communications	8%	25%	3.7%	10%
Construction	3%	16%	6.0%	2%
Hotels/Restaurants	8%	11%	4.1%	14%
Manufacturing	13%	18%	7.4%	12%
Mining	2%	32%	0.3%	0%
Real Estate	17%	22%	37.4%	16%
Social/Health Services	1%	36%	1.3%	4%
Other Services	9%	19%	6.0%	23%
Transportation	10%	24%	5.4%	4%
Utilities	14%	20%	12.6%	16%
Wholesale/Retail Trade	10%	19%	11.8%	9%
Other	4%	25%	2.3%	8%
Total	100%	20%	100.0%	12%

Notes: This table reports the sample composition by sector.

variables are assigned to the loan LGD, the 'year of default' and the 'year of peak cash flow'. The LGD itself does not change, as it is consistently computed based on all cash flows collected after the default event. Table 4 below illustrates the data structure. The dependant variable is always the loan level LGD at resolution. The time subscript of the macroeconomic variables refer either to the 'year of default' or the 'year of peak cash flow'. The time required to resolve a defaulted loan and collect all associated cash flows can vary significantly, ranging from 3 to 15 years, depending on factors such as the country, the exposure class and the specific recovery processes involved.[2] This variation in resolution time highlights the importance of considering different time points for macroeconomic variables. By examining both the 'year of default' and the 'year of peak cash flow', we aim to capture the potential impact of macroeconomic conditions on the LGD calculation more comprehensively.

The 'year of peak cash flow', Year_{CF}, refers to a concept similar to the Macaulay duration of bonds. The cash flow weighted time or the year of peak cash flow represents the weighted average of all relevant points in time between the default event and the time when cash flows were received by the bank.

$$\text{Year}_{\text{CF}} = \frac{\sum_{t=1}^{T} t \cdot CF_t}{\sum_{t=1}^{T} CF_t} \tag{1}$$

Figure 2 illustrates the concept. As depicted, the cash flows associated with loan resolution are concentrated around the 'year of peak cash flow', rather than in the 'year of default'. Thus, the relation between loan LGD and the macroeconomic environment appears to be economically more meaningful when analysed

[2]See ECB TRIM Report.

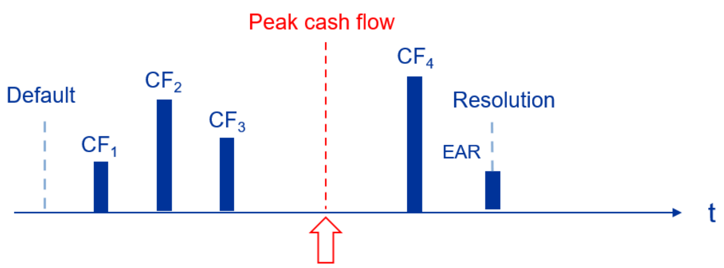
Table 4: Illustration of the dataset structure

Loan	Dependent variable	Year of Predictor variable (relative)		Year of Predictor variable (absolute)	
		Year of default	Year of peak cash flow	Year of default	Year of peak cash flow
Loan 1	$LGD_{1,2019}$	GDP_{t-5}	GDP_{t-2}	GDP_{2014}	GDP_{2017}
Loan 2	$LGD_{2,2019}$	GDP_{t-2}	GDP_{t-1}	GDP_{2017}	GDP_{2018}
Loan 3	$LGD_{3,2019}$	GDP_{t-5}	GDP_{t-2}	GDP_{2014}	GDP_{2017}
Loan 4	$LGD_{4,2018}$	GDP_{t-5}	GDP_{t-3}	GDP_{2013}	GDP_{2015}
Loan 5	$LGD_{5,2018}$	GDP_{t-6}	GDP_{t-4}	GDP_{2012}	GDP_{2014}
Loan 6	$LGD_{6,2018}$	GDP_{t-5}	GDP_{t-2}	GDP_{2013}	GDP_{2016}
Loan 7	$LGD_{7,2017}$	GDP_{t-2}	GDP_{t-1}	GDP_{2015}	GDP_{2016}
(...)	(...)	(...)	(...)	(...)	(...)

Notes: This table illustrates the structure of the dataset employed for conducting the regression analyses and obtaining the reported estimates.

in the context of the 'year of peak cash flow'.

Figure 2: Timing of LGD cash flows



Notes: This chart illustrates the timing of LGD cash flows during the period between the initial default event and the ultimate resolution of the loan.

To analyse the potential impact of macroeconomic conditions on LGD, we incorporate the following macroeconomic variables as predictors in our analysis: real GDP growth, house price growth, stock returns, unemployment rate and changes in the long-term interest rate. These variables are sourced from the European Central Bank (ECB) Statistical Data Warehouse. The selection of these variables is based on their potential influence on the recovery process and the overall economic environment in which defaulted loans are resolved. For instance, real GDP growth and unemployment rates capture the overall economic conditions affecting the recovery process, while house price growth and stock returns influence collateral values. Changes in long-term interest rates are included as they can impact borrowing costs and the discounting of future cash flows. By incorporating these macroeconomic predictors, our analysis aims to quantify their potential impact on LGD and provide insights into the relation between macroeconomic conditions and recovery outcomes for defaulted loans.

4 Empirical setup

This section outlines the empirical setup. We estimate the following regression using the ordinary least squares (OLS) method:

$$Y_l = \alpha + \beta_1 X'_{i,t} + \beta_2 Cure_i + +\varepsilon_{i,t}, \tag{2}$$

The dependent variable (Y_l) is a continuous variable over the interval [0,1] representing the LGD. $X'_{i,t}$ is a vector of macroeconomic variables for country i at time t. $X'_{i,t}$ includes real GDP growth, house prices growth, stock returns, unemployment rate and long-term interest rate changes. $Cure_{i,t}$ is a dummy variable taking the value 1 if a loan was cured and 0 otherwise. α is the intercept and $\varepsilon_{i,t}$ is the individual error term.

There are two limitations of the OLS estimation in equation 2. First, the predicted values from the OLS regression cannot be guaranteed to lie within the unit interval, while the LGD is defined over [0,1]. Second, the distribution of cumulative recovery rates (or LGD) displays a bimodal distribution, with two clusters around 0 and 1, implying that an estimation by OLS may result in a poor model fit (see Yashkir and Yashkir (2013) for an overview). Therefore, the OLS regression (equation 2) may not be a suitable specification. A common econometric technique for overcoming the limitations of the OLS specification above is a transformation of the left-hand side of equation 2 of the type $E(y|X')_{i,t} = G(\beta_k X')_{i,t}$, where function G is defined over [0,1]. This ensures that the predicted LGD lies between 0 and 1. Relying on the fractional response model as in Dermine and Carvalho (2006) and Bastos (2010),[3] we transform the left-hand

[3]By adopting this fractional response model approach, we not only ensure the validity of our estimates but also enhance the model's ability to capture the bimodal distribution of the LGD data.

side of equation 2 via the logistic function, as follows:

$$G(\beta_k X'_{i,t}) = \frac{\exp(\beta_k X'_{i,t})}{1 + \exp(\beta_k X'_{i,t})}, \tag{3}$$

The estimates β_k are derived through the maximisation of the Bernoulli log-likelihood function (Papke and Wooldridge, 1996):

$$l_{i,t}(\hat{\beta}_k) = y_i log[G(\hat{\beta}_k X'_{i,t})] + (1 - y_i) log[1 - G(\hat{\beta}_k X'_{i,t}))]. \tag{4}$$

We estimate equations 2 and 4 separately for the specification with macroeconomic variables in the 'year of default' and the 'year of peak cash flows' for both secured and unsecured loans. Effectively this means that the time subscript t is equal to the year of default for the 'year of default' estimation and peak cash flow for 'year of peak cash flow' estimation. We repeat the four estimations above using either simple OLS or the fractional response regression.

5 Results

The regression results from equations 2 and 4 are presented separately for secured and unsecured LGD in Tables 5 and 6, respectively. Table 5 displays the regression results with secured LGD as the dependent variable, whereas Table 6 shows the results of the regression having LGD unsecured as the dependent variable. In each table, columns (1) and (2) report the results from the OLS estimation, while columns (3) and (4) present the results from the fractional response regression. For each estimation method, the results are presented for both 'year of peak cash flow' and 'year of default', respectively.

The results presented in Tables 5 and 6 provide evidence that both secured and unsecured LGD tend to increase as macroeconomic conditions deteriorate, lending support to our first hypothesis. Table 5 shows that across the four specifications considered, an increase in unemployment and a decrease in stock returns are associated with a higher LGD. Specifically, an increase in the unemployment rate by one standard deviation is associated with a 1% increase in the LGD, while a one standard deviation increase in stock returns is associated with a 10% decrease in the LGD. Long-term interest rates and house price growth are significant in different model estimations: an increase in long-term interest rates is associated with a higher LGD in the specification that uses macroeconomic variables assigned to the LGD in the 'year of peak cash flow' as a dependant variable, while a decrease in house prices increases the LGD in the estimation with the 'year of default' specification. GDP growth is significant in 3 out of 4 specifications, but the sign of the coefficient estimate is counterintuitive.

The interpretation of the results for the secured LGD is intuitive: a deterioration in macroeconomic conditions leads to a decrease in collateral value, thereby increasing the LGD. In turn, the mechanism is less evident for the unsecured LGD. The unsecured LGD could be directly affected by macroeconomic conditions. For instance, an increase in unemployment deteriorates borrowers' repayment capacity, leading to a higher unsecured LGD. Alternatively, the effect of macroeconomic conditions could be correlated with unobserved country characteristics affecting the LGD. One relevant country characteristic could be the efficiency of the resolution framework. Thus, as a robustness check, we include country and bank fixed effects in equation (2) to test whether there is a direct impact of macroeconomic conditions on the LGD (discussed in greater detail in Section 6). The results remain qualitatively unchanged, suggesting that unsecured LGD is directly affected by macroeconomic conditions, rather than being driven by unobserved country-level factors.

Table 5: LGD of loans secured by real estate

Model	(1)	(2)	(3)	(4)
	OLS		**Fractional Response**	
Dependent Variable: LGD	Peak cash flow	Year of default	Peak cash flow	Year of default
Intercept	0.11***	0.13***	-1.97***	-1.97***
	(0.02)	(0.02)	(0.16)	(0.15)
Real GDP growth	0.97**	0.43	8.33***	6.68*
	(0.32)	(0.37)	(2.35)	(3.13)
Δ Unemployment rate	0.01***	0.01***	0.06***	0.07***
	(0.00)	(0.00)	(0.02)	(0.02)
Δ Long-term interest rate	0.03**	0.00	0.19**	0.00
	(0.01)	(0.01)	(0.06)	(0.06)
House prices growth	0.08	-0.50**	-0.12	-4.79***
	(0.16)	(0.16)	(1.28)	(1.25)
Stock returns	-0.10*	-0.20***	-0.88**	-1.33***
	(0.04)	(0.03)	(0.31)	(0.24)
Cured	-0.17***	-0.20***	-	-
	(0.02)	(0.02)	-	-
Number of observations	1332	1344	1158	1172
R-Square	8%	10%	-	-
F-Value	20.04	24.27	-	-

Notes: This table presents the estimates of the OLS model and fractional regression having the secured LGD as a dependant variable and macroeconomic variables as predictors. The dependent variable is defined as the average LGD in percent. Columns (1) and (3) report results for the regressions with macroeconomic variables entering the regression in the 'year of peak cash flow' . Columns (2) and (4) report results for the regressions with macroeconomic variables entering the regression in the 'year of default' . Standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 5 shows that the sensitivity to macroeconomic conditions is more pronounced for the secured LGD compared to the unsecured LGD. For unsecured LGD, only two variables are significantly related to the LGD across the four specifications (with the expected sign): GDP growth in the 'year of peak cash flow' estimation and stock returns in the 'year of default' estimation. Column (1) indicates that an increase in GDP growth by one standard deviation is associated with a 0.5% decrease in the LGD.

Results in Tables 5 and 6 suggest that there is no significant difference in the pattern of results between the 'year of default' estimation and the 'year of cash flow' estimation (columns (1) and (3) compared to columns (2) and (4) in each table). Thus, we do not find evidence to support our second and third hypotheses: the timing of cash flows does not seem to affect the sensitivity of the LGD to macroeconomic conditions. This could be due to the fact that our sample only includes large corporate borrowers with a more efficient resolution capacity: the mean LGD in our sample is 21.5% and the median time to recovery is 1.6 years. Overall, macroeconomic variables, together with the cure rate indicator, explain around 10% of the LGD variance, suggesting that borrower-specific factors and facility characteristics play a more important role.

Table 6: LGD of loans not secured by real estate

Model	(1)	(2)	(3)	(4)
	OLS		**Fractional Response**	
Dependent Variable: LGD	Peak cash flow	Year of default	Peak cash flow	Year of default
Intercept	0.26***	0.26***	-1.01***	-1.07***
	(0.01)	(0.01)	(0.10)	(0.09)
Real GDP growth	-0.50*	-0.07	-3.21*	0.19
	(0.21)	(0.23)	(1.52)	(1.64)
Δ Unemployment rate	0.00	0.00	-0.01	0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Δ Long-term interest rate	0.01	0.01	0.08	0.07
	(0.01)	(0.01)	(0.05)	(0.04)
House price growth	0.17	0.29**	0.67	1.61*
	(0.11)	(0.11)	(0.75)	(0.73)
Stock returns	-0.01	-0.10***	-0.11	-0.60***
	(0.03)	(0.02)	(0.18)	(0.14)
Cured	-0.24***	-0.24***	-	-
	(0.01)	(0.01)	-	-
Number of observations	5918	6057	4672	4814
R-Square	9%	9%	-	-
F-Value	92.27	101.75	-	-

Notes: This table presents the estimates of the OLS model and fractional regression having the unsecured LGD as a dependant variable and macroeconomic variables as predictors. The dependent variable is defined as the average LGD in percent. Columns (1) and (3) report results for the regressions with macroeconomic variables entering the regression in the 'year of peak cash flow' . Columns (2) and (4) report results for the regressions with macroeconomic variables entering the regression in the 'year of default' . Standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

6 Robustness tests

This section presents the robustness tests performed to validate the findings of our analysis. Tables 7 and 8 report the secured and unsecured LGD results, respectively, from the OLS estimation specified in equation (2), incorporating bank and country fixed effects. The results remain broadly consistent with our main findings. Columns (1) and (2) show the results with country fixed effects, while Columns (3) and (4) report the results with bank fixed effects. Table 7 confirms our previous set of results for the secured LGD. Across both country and bank fixed effects estimations, the main macroeconomic drivers of secured LGD remain unchanged, further reinforcing our findings. Table 8 shows that the unsecured LGD exhibits a negative correlation with GDP growth in the peak cash flow estimation and a negative correlation with stock price returns in the year of default estimation. This pattern of results remains consistent across the different fixed effects specifications.

Overall, the robustness tests conducted by incorporating bank and country fixed effects provide additional confidence in the validity and stability of our results, as the main patterns and relationships between macroeconomic factors and LGD persist across these alternative model specifications.

To test if the higher magnitude of macro coefficients for secured compared to unsecured LGD is statistically significant, we introduced an interaction term between the secured LGD dummy and the macro variables. This interaction term was included in a regression type as shown in equation (2), after pooling together observations for both secured and unsecured LGD. Table 9 presents the estimations for 'year of peak cash flow' and 'year of default'. For the 'year of default' estimation, the interaction term is significant and displays the expected sign for stock returns, house price growth and unemployment rate. This suggests that the relation between these macros and realised LGD is stronger for secured LGD compared to unsecured. For the 'year of peak cash flow' estimation, the interaction term for unemployment rate is significant and has the expected sign. Together, these results indicate that secured loans exhibit higher sensitivity to macroeconomic conditions compared to unsecured LGD.

Table 7: Robustness test - LGD of loans secured by real estate

Model	(1)	(2)	(3)	(4)
	Country FE		**Bank FE**	
Dependent Variable: LGD	Peak cash flow	Year of default	Peak cash flow	Year of default
Intercept	0.13***	0.17***	0.11***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Real GDP growth	0.87*	-0.09	0.97**	0.43
	(0.35)	(0.45)	(0.32)	(0.37)
Δ Unemployment rate	0.01***	0.01*	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ Long-term interest rate	0.03**	0.00	0.03**	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
House prices growth	0.21	-0.38*	0.08	-0.5**
	(0.19)	(0.19)	(0.16)	(0.16)
Stock returns	-0.08	-0.23***	-0.10*	-0.20***
	(0.05)	(0.04)	(0.04)	(0.03)
Cures	-0.18***	-0.21***	-0.17***	-0.20***
	(0.02)	(0.02)	(0.02)	(0.02)
N	1165	1177	1332	1344
R^2	9%	11%	8%	10%
F-Value	18.87	23.05	20.04	24.27

Notes: This table presents the estimates of the OLS model for the secured LGD as dependant variable and macroeconomic variables as predictors, including country fixed effects (Columns (1) and (2)) and bank fixed effects (Columns (3) and (4)). The dependent variable is defined as the average LGD in percent. Columns (1) and (3) report results for the regressions with macroeconomic variables entering the regression in the 'year of peak cash flow'. Columns (2) and (4) report results for the regressions with macroeconomic variables entering the regression in the 'year of default'. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 8: Robustness test - LGD of loans not secured by real estate

Model	(1)	(2)	(3)	(4)
	Country FE		**Bank FE**	
Dependent Variable: LGD	Peak cash flow	Year of default	Peak cash flow	Year of default
Intercept	0.26***	0.26***	0.26***	0.26***
	(0.01)	(0.01)	(0.01)	(0.01)
Real GDP growth	-0.55**	-0.13	-0.50*	-0.07
	(0.21)	(0.24)	(0.21)	(0.23)
Δ Unemployment rate	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Δ Long-term interest rate	0.01	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
House prices growth	0.16	0.24*	0.17	0.29**
	(0.11)	(0.11)	(0.11)	(0.11)
Stock returns	0.01	-0.11***	-0.01	-0.10***
	(0.03)	(0.02)	(0.03)	(0.02)
Cured	-0.24***	-0.24***	-0.24***	-0.24***
	(0.01)	(0.01)	(0.01)	(0.01)
N	5684	5823	5918	6057
R^2	8%	9%	9%	9%
F-Value	83.75	91.78	92.27	101.75

Notes: This table presents the estimates of the OLS model for the unsecured LGD as dependant variable and macroeconomic variables as predictors, including country fixed effects (Columns (1) and (2)) and bank fixed effects (Columns (3) and (4)). The dependent variable is defined as the average LGD in percent. Columns (1) and (3) report results for the regressions with macroeconomic variables entering the regression in the 'year of peak cash flow'. Columns (2) and (4) report results for the regressions with macroeconomic variables entering the regression in the 'year of default'. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 9: Robustness test - LGD secured versus unsecured

Model	(1)	(2)
Dependent Variable: LGD	Peak cash flow	Year of default
Intercept	0.27***	0.26***
	(0.02)	(0.02)
Real GDP growth	-0.60*	-0.03
	(0.25)	(0.29)
Δ Unemployment rate	0.00	0.00
	(0.00)	(0.00)
Δ Long-term interest rate	0.01	0.01
	(0.01)	(0.01)
House prices growth	0.20	0.35**
	(0.13)	(0.13)
Stock returns	-0.01	-0.12***
	(0.03)	(0.03)
Real GDP growth x Secured	1.88***	0.61
	(0.53)	(0.60)
Δ Unemployment rate x Secured	0.01**	0.01**
	(0.00)	(0.00)
Δ Long-term interest rate x Secured	0.02	-0.01
	(0.01)	(0.01)
House prices growth x Secured	-0.18	-0.95***
	(0.27)	(0.25)
Stock returns x Secured	-0.11	-0.11*
	(0.06)	(0.05)
Secured dummy	-0.16***	-0.14***
	(0.04)	(0.03)
Number of observations	5848	6007
R-Square	2%	1%
F-Value	11.04	6.73

Notes: This table presents the coefficient estimates of the OLS model having the LGD as dependant variable and macroeconomic variables as predictors. Secured is a dummy variable that takes the value 1 if a loan is secured by real estate and 0 otherwise. Column (1) reports results for the regressions with macroeconomic variables entering the regression in the 'year of peak cash flow'. Column (2) reports results for the regressions with macroeconomic variables entering the regression in the 'year of default'. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

7 Conclusion

Regulatory standards for estimating downturn LGD rely on macroeconomic variables; therefore, banks' regulatory models for capital requirements or stress testing generally assume that LGD deteriorates in line with macroeconomic conditions. However, empirical evidence on the relation between LGD and macroeconomic conditions is not conclusive. The different results across the literature may be driven by small sample sizes, cross-country differences, and differences in the econometric methods used. To the best of our knowledge, this research represents the first comprehensive study to use time-series data on cash flow-based recovery rates to investigate the sensitivity of LGD to macroeconomic conditions within the broader European context.

In this study, we propose an additional explanation for the weak relation between LGD and macroeconomic conditions observed in previous research. We reasoned that prolonged resolution times, coupled with the disincentive to liquidate collateral during market downturns, could potentially weaken the relation between macroeconomic conditions at the time of default and the realised LGD. This is because the LGD does not materialise instantaneously but rather unfolds over an extended period, during which macroeconomic conditions may fluctuate. This temporal dynamic could potentially obscure the relationship between LGD and macroeconomic conditions at the time of default, as the ultimate recovery process is influenced by evolving economic factors. To account for this temporal aspect, we assign the LGD to macroeconomic conditions at two distinct points in time: 'the year of default' and 'the year of peak cash flows'.

Our study yields compelling results, shedding light on the relation between LGD and macroeconomic conditions at different stages of the recovery process. Our results indicate that LGD responds to macroeconomic conditions both in 'the year of default' and in 'the year of peak cash flows'. Notably, the sensitivity to macroeconomic conditions is more pronounced for secured LGD compared to unsecured LGD. This finding underscores the potential impact of collateral and its value on the recovery process, which may be influenced by economic conditions. The unemployment rate and stock returns emerge as the most relevant macroeconomic variables affecting secured LGD. In addition, house prices and long-term interest rates are significant variables in 'the year of peak cash flow' and 'the year of default' estimations, respectively. For unsecured LGD, GDP growth and stock returns are the most relevant macroeconomic variables in 'the year of peak cash flow' and 'the year of default' estimations, respectively. These findings contribute to a deeper understanding of the intricate relation between LGD and macroeconomic conditions, highlighting the importance of considering both the secured nature of exposures and the temporal dynamics of the recovery process. By identifying the key macroeconomic drivers influencing LGD at different stages of the recovery process, our study offers valuable insights for regulators and the financial sector. These insights have the potential to inform and enhance various critical areas, including policy regulation, bank risk management practices, stress testing methodologies, and capital adequacy assessments.

Future studies could test the relevance of the timing of LGD cash flows by relying on a more diverse sample, encompassing small to medium enterprises (SMEs) or household mortgages. Furthermore, given the moderate explanatory power of macroeconomic variables in our model, future research could extend the estimation by including borrower and facility-level variables. Additionally, investigating the impact of the COVID-19 pandemic on LGD cash flows could offer valuable insights into the impact of different types of economic crises on default patterns and the timing of cash flows, providing a comprehensive understanding of the relationship between LGD and macroeconomic factors.

References

Altman, E. (2006). Default recovery rates and LGD in credit risk modeling and practice: an updated review of the literature and empirical evidence. *NYU Salomon Center working paper*.

Bastos, J. (2010). Forecasting bank loans loss-given-default. *Journal of Banking and Finance*, 34:2510–2517.

Bellotti, T. and Crook, J. (2012). Bias-corrected matching estimators for average treatment effects. *International Journal of Forecasting*, 28:172–1821.

Betz, J., Krüger, S., Kellner, R., and Rösch, D. (2020). Macroeconomic effects and frailties in the resolution of non-performing loans. *Journal of Banking and Finance*, 112:1–26.

Bruche, M. and González-Aguado, C. (2010). Bias-corrected matching estimators for average treatment effects. *Journal of Banking and Finance*, 34:754—-76.

Brumma, N. and Winckle, P. (2017). Downturn lgd study 2017. *Global Credit Data*.

Calem, P. and LaCour-Little, M. (2004). Risk-based capital requirements for mortgage loans. *Journal of Banking and Finance*, 28:647–672.

Caselli, S., Gatti, S., and Querci, F. (2008). The sensitivity of the loss given default rate to systematic risk: New empirical evidence on bank loans. *Journal of Financial Services Research*, 34:1–34.

Dermine, J. and Carvalho, C. (2006). Bank loan losses-given default: A case study. *Journal of Banking and Finance*, 30:1219–1243.

Grünert, J.and Weber, M. (2009). Recovery rates of commercial lending : empirical evidence for german companies. *Journal of Banking and Finance*, 30:505–513.

Gupton, G. M. and Stein, R. M. (2005). Losscalc: Model for predicting loss given default (lgd). *Moody's KMV Company*.

Ingermann, P., Hesse, F., Belorgey, C., and Pfingsten, A. (2016). The recovery rate for retail and commercial customers in germany: a look at collateral and its adjusted market values. *Business research*, 9:179–228.

Konecny, T., Seidler, J., Belyaeva, A., and Belyaev, K. (2017). The time dimension of the links between loss-given-default and the macroeconomy. *ECB Working paper No 2037*.

Krüger, S. and Rösch, D. (2017). Downturn lgd modeling using quantile regression. *Journal of Banking and Finance*, 79:42–56.

Lekkas, V., Quigley, J. M., and Order., R. V. (1993). Loan loss severity and optimal mortgage default. *Journal of Banking and Finance*, 21(4):353–371.

Qi, M. and Yang, X. (2007). Loss given default of high loan-to-value residential mortgages. *Journal of Banking and Finance*, 35(5):788–799.

Qi, M. and Zhao, X. (2011). Comparison of modeling methods for loss given default. *Journal of Banking and Finance*, 35(11):2842–2855.

Yashkir, O. and Yashkir, Y. (2013). Loss given default modeling: a comparative analysis. *Journal of Risk Model Validation*, 7(1):25–59.

Acknowledgements

We would like to thank the anonymous referee, participants at the ECB internal seminar as well as participants at the IAAE Conference in Thessalonki, Greece for helpful comments. The opinions in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank or the Eurosystem.
We would like to thank Global Credit Data for providing the data for this study, particularly Nina Brumma (nina.brumma@globalcreditdata.org) and Nunzia Rainone for extracting the relevant data.

Benjamin Galow
d-fine GmbH, Frankfurt am Main, Germany; email: benjamin.galow@d-fine.com

Oana-Maria Georgescu
European Central Bank, Frankfurt am Main, Germany; email: oana_maria.georgescu@ecb.europa.eu

Aurea Ponte Marques
European Central Bank, Frankfurt am Main, Germany; email: aurea.marques@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

PDF ISBN 978-92-899- 6764-8 ISSN 1725-2806 doi:10.2866/10039 QB-AR-24-071-EN-N