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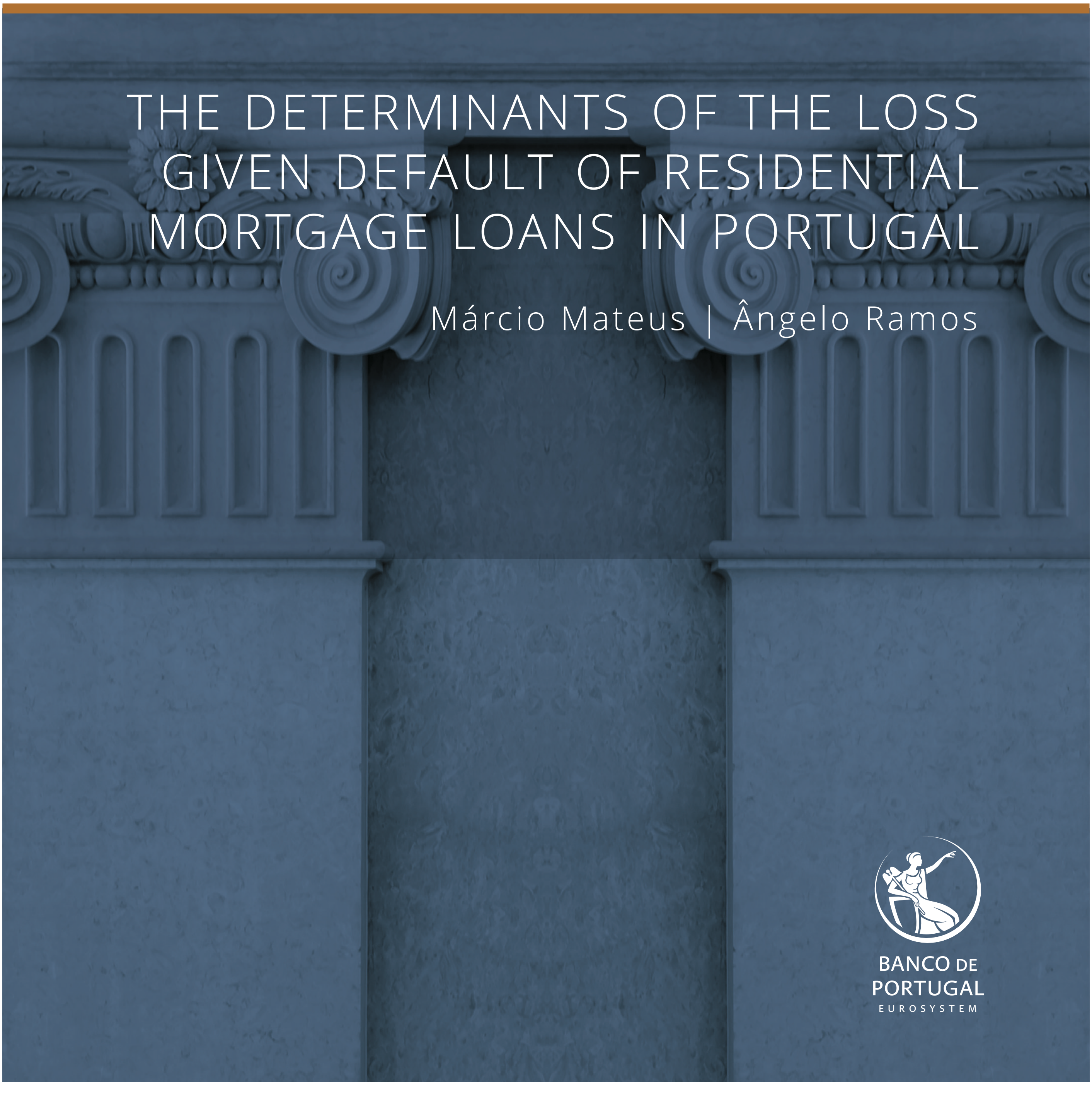

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SEPTEMBER 2023

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The determinants of the loss given default of residential mortgage loans in Portugal

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Abstract
In this paper we investigate the determinants of the loss given default (LGD) of mortgage loans in Portugal. Exploring loan-level data from the Portuguese Central Credit Register, we show that the original LTV (oLTV) ratio is by far the most important determinant of the LGD of mortgage loans, but the relation between these two variables is not linear. A higher oLTV ratio is associated with a higher LGD of mortgage loans, but only above a certain threshold. We provide evidence that the critical area in the relationship between these two variables lies in a range between 80% and 100%. Our results also highlight the importance of the house price cycle history in explaining the LGD, with distinct short and long-term effects. In the short-term we find a negative correlation between house prices and LGD, meaning that a house price increase just before loan origination seems to contribute to the decrease of the LGD in the future. In the long-term the correlation is positive, which suggests that the higher the house price has increased in the past, the higher the future LGD is expected to be.

JEL: G21, G28

Keywords: Loss given default, residential mortgage loans, housing cycle, financial stability.

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1. Introduction

Credit risk relates to the possibility of a loss due to a borrower's failure to repay a loan or meet contractual obligations. The likelihood of loss materialization is associated with the borrower's probability of default (PD) while the severity of loss in the event of default is accounted for by the loss given default (LGD). Under Basel III regulation banks that decided to implement the Internal Ratings Based (IRB) approach are allowed to use their own quantitative models to estimate the PD, LGD and other parameters required to estimate the risk weighted assets and total regulatory capital. There have been many studies on PD determinants, but research on LGD remains somehow limited in the literature. In addition, few studies have focused on retail exposure such as residential mortgages, mostly because public data is not easily available. This paper focuses on the determinants of the LGD of residential mortgages, using granular data from the Portuguese Central Credit Register (CCR), which contains monthly loan-level information on all lending relationships between Portuguese credit institutions and Portuguese households.

Among the limited literature that focuses on the LGD of residential mortgages, most have focused on testing theories about LGD and the factors that affect it. Lekkas *et al.* (1993) test empirically the frictionless options-based mortgage default theory. The authors find that an increased loss severity of residential mortgages is associated with higher original LTV (oLTV) ratio, the geographical location, and the time elapsed since mortgage loans were originated. Pennington-Cross *et al.* (2003), and Calem and LaCour-Little (2004) have also addressed the LGD determinants. Their results are aligned with those of Lekkas *et al.* (1993), that either the oLTV or current LTV (cLTV) ratios, mortgage age, and loan size are important determinants of the LGD. Qi and Yang (2009) study LGD of high LTV loans. They find that cLTV ratio is the single most important determinant of LGD and that mortgage loss severity in distressed housing markets is substantially higher than under regular housing market conditions. Zhang *et al.* (2010) finds that house price history had a long memory in explaining LGD after the subprime crisis and its explanatory power far exceeds the oLTV ratio and other characteristics.

The present paper contributes to the existing literature on LGD determinants in the following ways. First, we study the effect of the housing cycle and loan level variables on the LGD of mortgage loans. Our sample covers the most recent housing cycle, affected by the 2007-09 Global Financial Crisis (GFC) and by the sovereign debt crisis in Portugal. Second, we present evidence that the relationship between the oLTV ratio on the LGD of mortgage loans is non-linear, and that taking it into account can significantly improve the model fitting. This is particularly important since most regression models that use information at mortgage origination (such as oLTV ratio) suffer from poor model fit. Third, we estimate the thresholds for the discontinuity in the relationship between the LTV ratio and the LGD of mortgage loans. Lastly, as a simulation exercise, we analyze the impact on our results of a real estate bubble equal to that observed in Spain before the GFC.

We find that the oLTV ratio is by far the most important determinant of the LGD of mortgage loans. A higher oLTV ratio is associated with a higher LGD of mortgage loans, but only for loans with an oLTV ratio above 80%. Our threshold regression model confirms that the critical area in the relationship between LGD and oLTV ratio lies between 80% and 100%. The housing cycle history also plays a relevant role, with distinct short and long-term effects. A housing price appreciation just before loan origination reduces the future LGD, as a house price increase tends to have a positive short-term serial correlation. On the other hand, the long-term effect suggests that when housing cycles are endemic, the price appreciation increases the LGD. In this scenario, the higher the house price has increased in the past, the higher the future LGD is expected to be. Our results are thus consistent with research that shows that house prices exhibit serial correlation and mean reversion, where large market swings are usually followed by reversals to the unobserved fundamental price level (Capozza *et al.* (2004), and Gao *et al.* (2009)). Mean reversion implies that, in the long run, markets tend towards an equilibrium level, and high serial correlation can cause house prices to rise significantly beyond their equilibrium level and eventually to a decline in prices.

Finally, when we replace the evolution of housing prices observed in Portugal with those recorded in Spain during the same period i.e., assuming Portugal recorded a housing bubble before the GFC, our main conclusions do not change significantly. As expected, the explanatory power of house price history increases at the expense of the oLTV ratio, but the oLTV ratio remains by far the most important determinant of LGD.

Our analysis and results offer insights to macro and microprudential authorities. From a macroprudential perspective, our results are particularly relevant. We provide evidence that the critical area in the relationship between LGD and oLTV lies between 80% and 100%. As an increasing number of countries have adopted borrower-based measures, which typically include limits on the LTV ratio of new mortgages, this result provides some clues about the range within which this ratio should lie. On what concerns the microprudential regulation, the estimated LGD is one of the main inputs to estimate risk weights under the IRB approach, with an impact on the amount of regulatory capital required in percentage of risk weighted assets. Given the mean reversion pattern of house prices towards an equilibrium level in the long run, our results support the estimation of a through-the-cycle LGD in the spirit of the Basel framework. Not taking into account the housing cycle in the estimation of the LGD of mortgage loans could ultimately mean a misestimation of banks' actual regulatory capital and resilience. Finally, it is important to stress that even though our results are closely aligned with the literature on this topic, they provide empirical evidence that is valid for Portugal in a given time period and thus needs to be followed up with evidence for other countries and time periods before conclusions can be generalized.

The paper is organized as follows. We describe the data and provide descriptive statistics in section 2. In section 3 we present the methodology used to analyse the determinants of the LGD of mortgage loans, and in section 4 we discuss the respective results. In section 5, using a threshold regression, we identify thresholds for distinct effects of the oLTV ratio on the LGD of mortgage loans. In section 6, we perform a sensitivity analysis to the results obtained in sections 4 and 5, and in section 7 we conduct a simulation exercise on the impact of the Spanish housing bubble on our results. We conclude in section 8.

2. Data and descriptive statistics

This section presents the datasets and the descriptive statistics of the variables used in our analysis.

2.1. Datasets and variables

In this paper we analyze the determinants of the LGD of residential mortgage loans based on a sample of loans that were granted and defaulted between 2009 and 2019. Our main data source is the Portuguese Central Credit Register. This granular database, managed by the Banco de Portugal, provides monthly loan-level information on all lending relationships between Portuguese credit institutions and Portuguese households, and includes several loan-specific characteristics of interest, such as loan amount, origination and maturity date, the purpose of the contract, borrower's age, borrower's region, type, and value of the collateral (if any).

We provide variable definitions in Table A1. Our dependent variable is the LGD of each residential mortgage loan at default. For the purposes of this paper, a loan is considered to be in default if: (i) it recorded three consecutive months of overdue credit, and (ii) 2% or more of the loan amount is overdue. Following Gross and Población (2017), we assume the bank confiscates the collateral in case of default. The LGD under the confiscation scenario evolves dynamically as a function of house prices between the default period (T^d) and the confiscation period[1] (T^c). The LGD under the confiscation scenario was estimated as:

$$LGD = max\left(0; 1-\left(\frac{min(V^{T^c} \times (1-adcost) \times Discount; L^{T^d})}{L^{T^d}}\right)\right) \quad (1)$$

Where V^{T^c} stands for the adjusted collateral value (initial value of the collateral adjusted according to the evolution of the real estate prices)[2], L^{T^d} stands for outstanding loan amount at default, $adcost$ stands for administrative costs, and $Discount$ is the discount rate. As in Gross and Población (2017), we assume that

1. The confiscation time is the time to recover the collateral after the default.

2. The value of the property at confiscation time (V^{T^c}) is adjusted based on the house price variation between the time of default (T^d) and the time of confiscation (T^c), using a country-level house price index (HP): $V^{T^c} = e^{ln(V^{T^d})+ln(HP^{T^c}/HP^{T^d})}$

administrative costs correspond to 5% of the adjusted collateral value, and the confiscation time is two years ($c = 2$). This expression ensures that the LGD is zero if the value of the collateral is significantly higher than the loan amount at the time of default. We follow the literature's calibration on these two variables as there is no systematized data available for Portugal. The discount rate, which measures the opportunity cost for the bank between the time of default and the time of confiscation, was computed as:

$$Discount = \frac{1}{(1 + LTN)^c} \tag{2}$$

Where LTN is the yield of Portuguese 10-year Treasury bonds by the time of default and c is the confiscation time.

As explanatory variables, we include several borrower and loan-level features. Borrower-level variables include age at contract origination, number of bank relations, number of credit products, and the share of housing loans on the borrower's total bank debt. In cases where there is more than one borrower associated with the same contract, which happens very often in mortgage loans, only the first borrower is considered. Loan-level characteristics include the loan amount and maturity, the oLTV ratio, and a dummy variable equal to one if the loan has more than one collateral. All loan-level variables refer to the date of contract origination. In the case of loans for housing construction, we considered as the origination date when the bank loan reached its maximum instead of the date the contract started. Finally, we also include as explanatory variables the real house prices in Portugal, as a proxy for the housing cycle, the GDP per capita, and the year-on-year variation of the GDP per capita at the region (NUTS3) level. The time series on real house prices were obtained from the Organization for Economic Co-operation and Development (OECD) and data on regional GDP per capita is compiled and published by Statistics Portugal. Despite the extensive set of explanatory variables, we acknowledge that other potentially relevant variables, such as borrowers' income and wealth, may be missing. These variables were not included because they were not available in the Portuguese Central Credit Register in the period under analysis or other databases to which we had access.

2.2. Descriptive statistics

The indebtedness ratio of Portuguese households increased significantly between 2000 and 2009, peaking at 126% of disposable income in 2009, mainly reflecting the strong growth in loans for house purchase. Following the Financial Assistance Programme between the Portuguese authorities, the European Union (EU) and the International Monetary Fund, the Portuguese economy initiated in 2011 an adjustment process of their macroeconomic imbalances. This process, which ultimately resulted in a strong contraction of domestic demand and of households' disposable income, implied a deleveraging of the Portuguese banking system. Against this background, the amount of new loans for house purchase fell significantly, reaching historic lows between 2012 and 2014, and the amount of households' overdue credit recorded an increase. After 2014, in a context of easing tensions in euro area sovereign debt markets, an increase in households' disposable income, the housing loans started a recovery trend and default rates started to ease. Our sample covers this full bust-and-boom cycle.

Table 1 presents the summary statistics. Our database has 12,777 residential mortgage loans that were originated and defaulted between 2009 and 2019. Most of the loans in the sample were granted in 2009 and 2010 and defaulted following the sovereign debt crisis (Figure A1). The average LGD was 8%, although it fluctuated significantly during the time span analyzed, increasing from around 5%, in 2009, to over 15% during the sovereign debt crisis, and then returning to levels of around 2% by the end of the sample period (Figure A2). The average LTV at contract origination was 87%, even though about one-third of the contracts have an LTV equal to 100% (Figure A3)[3]. Borrowers included in our sample have, on average, a relationship with two different banks and two different credit products. Most of the borrower's debt was in the form of housing loans, as the share of housing loans on the borrower's total bank debt was, on average, 88%. The average original balance was around 83 thousand euros and about 11% of the loans had more than one collateral. Data on loan maturity show that about half of the loans have a maturity of more than 30 years and about one-third have a maturity between 20 and 30 years (maturity data is only available by buckets). The average regional GDP per capita is about 17 thousand euros, with significant differences among regions. The average variation in GDP was close to zero.

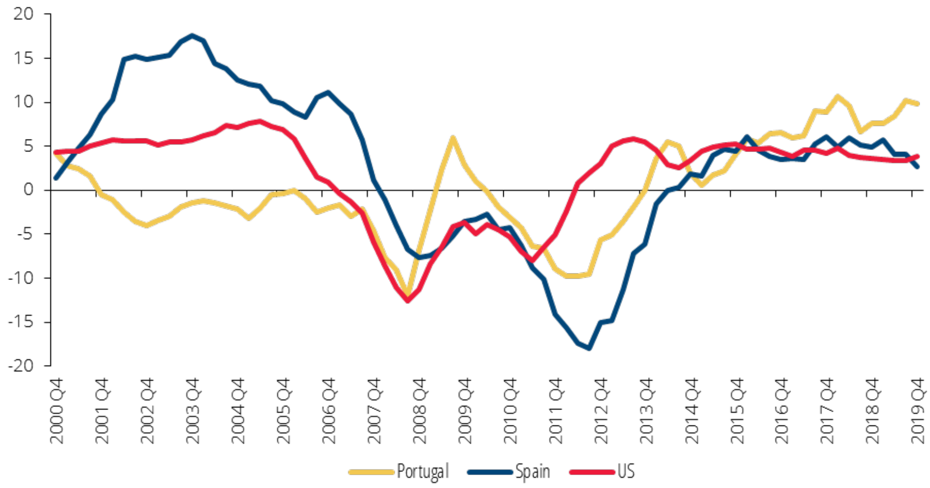
3. The value of the collateral considered to estimate the LTV ratio is the one reported in Portuguese CCR. Following the entry into force of the Macroprudential Recommendation, in July 2018, the limit to the oLTV ratio for the construction or purchase of own and permanent residence, which account for the largest share of the credit market, was set at 90%. The denominator of the LTV ratio was required to be calculated considering the minimum between the purchase price and the appraisal value of the immovable property pledged as collateral. Prior to the implementation of this measure, banks' standard practice was to set the oLTV ratio between 80 and 90% of the appraisal value. However, since the appraisal value was in general higher than the purchase price, in practice there was a substantial share of credit financed at 100% of the purchase price. Thus, the LTV ratio considered in our study is likely to be lower than it would have been if it had been calculated under the Recommendation. In addition, there were regulatory incentives for residential real estate exposures with lower LTV ratios, which could explain the significant oLTV ratios between 50% and 80%.

Table 1. Descriptive statistics

	N	Mean	Std.Dev.	25th pct.	Median	75th pct.
LGD (%)	12,766	8	13	0	0	16
LTV ratio at origination (%)	12,777	87	97	70	84	100
Borrower age at contract origination (years)	12,720	41	11	33	40	48
Number of bank relations	12,777	2	2	1	2	3
Number of credit products	12,777	2	1	2	2	3
Share housing loans (%)	12,777	88	16	83	94	100
Loan amount at origination (euros)	12,777	83,192	83,451	38,400	67,193	104,871
Other guarantee (besides the house)	12,777	0.11	0.31	0	0	0
Loan maturity: $\leq$10 years (dummy)	12,777	0.04	0.20	0	0	0
Loan maturity:]10 years,20 years] (dummy)	12,777	0.15	0.35	0	0	0
Loan maturity:]20 years,30 years] (dummy)	12,777	0.34	0.47	0	0	1
Loan maturity: $>$30 years (dummy)	12,777	0.47	0.50	0	0	1
Regional GDP per capita (euros)	12,713	17,424	4,574	14,233	15,774	23,485
Annual variation of GDP per capita (%)	12,713	-0.01	3.12	-2.27	-0.32	1.91
Real house price variation (%)	12,777	-1.81	5.49	-4.89	0.03	1.74

The real house prices variation was differentiated throughout the sample period. Between the beginning of 2009 and the end of 2013, real estate prices fell by about 15% in real terms. Between 2014 and 2019, house prices in Portugal grew by 46% in real terms (Figure 1). The more recent price dynamics of the residential real estate market have been driven by the improving household income, the low interest rate environment, demand by non-residents, the strong dynamics of the tourism sector, and the time lag between the supply-side response to an increase in demand in the short run. In the period preceding the beginning of our sample there was no evidence of house price overvaluation in Portugal, as prices recorded mostly negative annual variations. Portugal, unlike Spain or the United States, did not experience a real estate price bubble before the GFC (Figure 1).

Figure 1: Real house prices | Year-on-year variation, per cent



Source: Organization for Economic Co-operation and Development (OECD) (author's calculations). | Notes: House prices are seasonally adjusted. Real house prices are obtained from nominal house prices deflated using the private consumption deflator from the national account statistics.

3. Methodology

To study how the LGD is influenced by the housing cycle, and by borrower and loan-level characteristics, we estimate the following linear probability model:

$$\begin{aligned} LGD_{i,t,t+k} = \beta_0 + \beta_1 \times hpa_{t-1} + B_2 \times hpa_{t-j} + B_3 \times X_{i,t} + B_4 \times Y_{r,t} + \\ \gamma_r + \delta_b + \varepsilon_{i,t} \end{aligned} \tag{3}$$

The dependent variable is the Loss Given Default of loan i, granted at time t, and defaulted at time $t+k$. The housing cycle effect is controlled for by including as explanatory variable the annualized house price variation at the time (previous quarter) the loan was granted (hpa_{t-1}) and the lags up to 24 quarters (j), in intervals of 4 quarters, prior to the granting of the loan, i.e., $j = 4, 8, 12, 16, 20, 24$ (hpa_{t-j}). We chose seven lags as we intended to capture the housing market trend prior to the loan origination date without over-fitting the model. The coefficient β_1 and those in the vector of coefficients B_2 measure the impact of the housing cycle on the LGD. The vector $X_{i,t}$ contains a set of control variables at the borrower and loan-level characteristics (oLTV ratio, borrower's age, loan amount, loan maturity, number of bank relations, number of credit products, share of housing loans on borrower's total debt and a dummy variable equal to 1 if the loan has another guarantee besides the house). The vector $Y_{r,t}$ includes variables that control for the economic activity and the business cycle at region level (GDP per capita and the year-on-year variation of the GDP per capita at time t and region in r

(NUTS3)). Region (γ_r) and bank (δ_b) fixed effects are also introduced to control for time-invariant region and bank heterogeneity. The former effects are controlled in the regression by including binary variables for the NUTS3 of the borrower. The error term is represented by ($\varepsilon_{i,t}$). Standard errors are clustered at the bank-level. Estimations are done using Stata's reghdfe (Correia (2017)).

4. Results

4.1. The drivers of the LGD of residential mortgage loans in Portugal

In this section we analyze how housing market fluctuations, the oLTV and other variables affect the LGD of mortgage loans. The results are presented in Table 2. The estimates suggest a distinct short and long-term effects of the house price cycle on the LGD of mortgage loans. In the short-term we find a negative correlation between house prices and the LGD of mortgage loans, meaning that a house price increase just before loan origination seems to contribute to the decrease of the LGD in the future. This result is intuitive, as a house price increase tends to have a positive short-term serial correlation. Thus, a house price appreciation will usually continue in the short run, increasing the value of the house. This price effect, in tandem with the reduction of the amount of the loan due to amortization, leads to a lower LGD in the future. On the other hand, the long-term effect (four years or more) is negative, which suggests that the higher the house price has increased in the past, the higher the future LGD is expected to be. An increase in house prices 16, 20, and 24 quarters prior to loan origination, increases LGD. Our results are thus consistent with the mean-reversion pattern of house prices and with near-term serial correlation (Capozza *et al.* (2004), and Gao *et al.* (2009)). The results are robust to different specifications of the econometric model (controlling for the oLTV ratio, including loan, borrower, and macro effects, and bank and region fixed effects).

Table 2. Regression of LGD on housing market cycle, loan and borrower characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
hpa_{t-1}	-0.315*	-0.354*	-0.371***	-0.288***	-0.282***	-0.337***
	(0.132)	(0.135)	(0.105)	(0.055)	(0.054)	(0.073)
hpa_{t-4}	-0.056	-0.063	-0.038	0.017	0.013	-0.018
	(0.043)	(0.033)	(0.022)	(0.010)	(0.009)	(0.010)
hpa_{t-8}	0.025	0.029	0.031	0.040	0.040	0.003
	(0.018)	(0.020)	(0.019)	(0.021)	(0.020)	(0.015)
hpa_{t-12}	-0.020	-0.013	-0.015	0.015	0.010	-0.005
	(0.039)	(0.032)	(0.027)	(0.014)	(0.016)	(0.015)
hpa_{t-16}	0.189	0.130	0.104	0.085**	0.077**	0.077**
	(0.097)	(0.072)	(0.065)	(0.029)	(0.027)	(0.028)
hpa_{t-20}	0.311**	0.278**	0.253**	0.283***	0.295***	0.295***
	(0.104)	(0.084)	(0.080)	(0.076)	(0.077)	(0.074)
hpa_{t-24}	0.286	0.193	0.156	0.220**	0.242**	0.227**
	(0.156)	(0.105)	(0.083)	(0.083)	(0.087)	(0.079)
oLTV (level)			0.001***			
			(0.000)			
D2(50%<oLTV≤70%)				-0.009***	-0.009***	-0.008***
				(0.002)	(0.002)	(0.002)
D3(70%<oLTV≤80%)				-0.006	-0.007*	-0.007*
				(0.004)	(0.003)	(0.003)
D4(80%<oLTV≤90%)				0.033***	0.031***	0.031***
				(0.005)	(0.003)	(0.003)
D5(90%<oLTV<100%)				0.097***	0.091***	0.091***
				(0.005)	(0.004)	(0.004)
D6(oLTV=100%)				0.134***	0.118***	0.119***
				(0.004)	(0.006)	(0.006)
D7(100%<oLTV≤110%)				0.156***	0.144***	0.144***
				(0.012)	(0.012)	(0.012)
D8(110%<oLTV≤120%)				0.204***	0.194***	0.196***
				(0.011)	(0.010)	(0.010)
D9(120%<oLTV≤150%)				0.326***	0.315***	0.316***
				(0.014)	(0.013)	(0.013)
D10(oLTV>150%)				0.632***	0.627***	0.626***
				(0.042)	(0.039)	(0.039)
Loan, borrower and macro controls (excluding LTV)	NO	YES	YES	YES	YES	YES
Bank FEs	NO	NO	NO	NO	YES	YES
Region FEs	NO	NO	NO	NO	NO	YES
Observations	12,766	12,702	12,702	12,702	12,692	12,692
adj. R-sq	0.025	0.097	0.328	0.678	0.684	0.687
AIC	-17,205.2	-18,047.5	-21,789.5	-31,133.4	-31,462.6	-31,602.0
BIC	-17,153.0	-17,920.8	-21,655.4	-30,939.7	-31,268.9	-31,408.3

Notes: For the oLTV dummy variables, the coefficients represent the discrete change from the base category (loans with an oLTV<50%). The standard errors are clustered at the bank-level. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively. Time period 2009-2019.

Our results also show that the oLTV ratio is the variable that improves the model fit the most. Including borrower and loan-level characteristics (except the oLTV ratio) increases the adjusted R squared from 0.025 (column 1) to 0.097 (column 2), while including the oLTV ratio rises the adjusted R squared to 0.328 (column 3). Although these results are aligned with those usually found in the literature, we were able to improve the model fitting just by changing the way oLTV is specified in the model. In fact, just by decomposing the oLTV ratio by different classes (column 4) we were able to boost the adjusted R squared to 0.678 (from 0.328), which suggests that the relationship between the oLTV ratio and the

LGD of mortgage loans in non-linear. An increase of the oLTV ratio is associated with a higher LGD of mortgage loans, but only for contracts with an oLTV ratio above 80%, as the differences between coefficients of oLTV classes below 80% are not economically meaningful, i.e. the classes between 50% and 80% are not significantly different (from an economic perspective) from the base category. Only above an oLTV ratio of 80%, the differences from the base category are both economically and statistically different. Compared with the base category (oLTV $\leq$ 50%), and assuming everything else constant, the LGD of a loan with an oLTV ratio between 80% and 90% is, on average, 3.3 p.p. higher, while the LGD of a loan with an oLTV ratio between 90% and 100% is, on average, 9.7 p.p. higher, and the LGD of a loan with an oLTV ratio equal to 100% is 13.4. p.p. higher. If 100% $<$ oLTV $\leq$ 110%, 110% $<$ oLTV $\leq$ 120%, 120% $<$ oLTV $\leq$ 150%, and oLTV $>$ 150%, average LGD is 15.6 p.p., 20.4 p.p., 32.6 p.p., and 63.2 p.p. higher, respectively. All these effects are statistically significant. Including bank (column 5) and bank and region fixed effects (column 6) does not significantly improve the model specification.

The implication of our results is twofold. First, they show that the housing cycle has a long memory and is a relevant determinant of LGD. Second, the LTV ratio of the contract at the time of loan origination is the single most important determinant of the LGD. Thus, our result suggest we can obtain a good prediction of mortgage loans LGD by the time they are originated. All we need to know is the oLTV ratio of the loan and the housing market history prior to loan origination.

5. Threshold regressions

In the previous section, we documented that the oLTV ratio is the most important determinant of LGD of mortgage loans and that the relationship between these two variables is not linear. Results suggest a significant increment in the LGD for loans with an LTV ratio above 80%. In this section we explore the idea that the LGD increases significantly for loans with an LTV ratio over a certain level, by estimating a threshold model. This approach has the advantage of taking an agnostic perspective to analyze nonlinearity in the relationship between the two variables, since it allows us to obtain an estimate of the threshold of the LTV ratio that best fits the data. Threshold models are part of a class of models that take the natural approach to modelling nonlinearity by setting different regimes and allowing for the relationship of the variables under study to depend on the prevailing regime. The point at which the data is split is defined with respect to a particular variable, in our study the oLTV ratio. Thus, in this section we use the threshold estimation framework proposed by Hansen (2000) to estimate the thresholds for the discontinuity in the relationship between the oLTV ratio and the LGD of mortgage loans in our sample. Appendix presents the methodological details regarding the threshold model.

Threshold models allow to estimate one or more discontinuity points between different regimes. We assumed two discontinuity points and we tested that: (i) only the constant or (ii) the constant and all the coefficients vary between the different regimes. According to our results, reported in Table 3, the threshold for the oLTV ratio that best fits the data is 93%, when only the constant varies, and 94% when the coefficients are also consented to vary. When we allow for a second threshold, the results suggest a value of 100%, whether we consider only the constant or that all the coefficients associated with the explanatory variables vary. The estimated thresholds are thus close to those suggested by the linear regression model, confirming that the critical area in the relationship between LGD and oLTV ratio lies between 80% and 90%. Finally, our results are also very much aligned with the limit of 90% to the LTV ratio of new permanent housing loans set by the Macroprudential Recommendation of Banco de Portugal in 2018.

Table 3. Threshold regression results for the discontinuity values in the relationship between the LTV ratio and LGD of mortgage loans

Only constant		Constant and explanatory variables	
Order	LTV ratio estimated threshold (%)	Order	LTV ratio estimated threshold (%)
1	93	1	94
2	100	2	100

Source: Author's calculations. | Notes: The threshold regression is based on the specification presented in column 3 of Table 2.

6. Sensitivity analysis and robustness checks

6.1. Sensitivity analysis to the drivers of the LGD of residential mortgage loans

In this section, we evaluate the robustness of our results from two different perspectives. First, we replicate the regressions excluding all credit institutions with a disproportionately high number of loans with an LTV ratio equal to 100%. The threshold for exclusion was set at 30%, which means that credit institutions with more than 30% of the loans with an LTV ratio equal to 100% were excluded from our sample. According to the CCR reporting manual, the value of the collateral to be reported should correspond as closely as possible to the book value of the underlying asset. However, in practice, some credit institutions seem to be assessing the value of the collateral as the appraisal value while others seem to be reporting the minimum between the loan amount and the appraisal value, as it corresponds to the maximum amount the credit institutions is expected to recover in case of default. The latter reporting procedure leads to a high share of loans with an

LTV equal to 100%. Our purpose with this exclusion is to assess whether the results are being driven by these different reporting practices. In other words, this analysis allows us to check if our findings remain valid when we exclude those credit institutions with a high share of loans with an LTV equal to 100%.

Second, we re-estimate the discount rate. The discount rate aims to measure the opportunity cost for the bank between the time of default and the time of confiscation and should be based on the risk-free rate. In practice, the risk-free rate is commonly considered to be equal to the interest paid on government Treasury bills. However, since our sample period covers the European sovereign debt crisis, which significantly affected Portugal's cost of financing, we redo our analysis considering as risk-free the German 10-year Treasury bond yield and, alternatively, the two-year euribor swap rate, instead of the Portuguese 10-year Treasury bonds yield. These two alternative interest rates allow us to purge the idiosyncratic risk of Portugal during this particular period, however, both rates become negative in the last years of our sample period. With this sensitivity analysis, we want to assess whether our main conclusions are being influenced by the high yield recorded by Portuguese 10-year Treasury bonds during the sample period.

Table 4 reports, in the first column, the results of our baseline specification (which corresponds to the results presented in column 6 of Table 2) and, in the other columns, the results of the sensitivity analyses performed. The estimates presented in the second column, excluding credit institutions with more than 30% of new loans with an LTV ratio equal to 100%, largely resembled those of baseline regression, even though we lost about 40% of the sample. This suggests that the results are robust and that the possible existence of different reporting procedures does not seem to bias our results in a significant way.

Replacing the Portuguese 10-year Treasury bonds yield by the German 10-year Treasury bond yield or by the two-year euribor swap rate has a greater impact on the results. The negative short-term effect between house prices and the LGD of mortgage continues to be visible in hpa_{t-1}, although the magnitude and the statistical significance of the coefficient has decreased, and has been extended to hpa_{t-8} and hpa_{t-12}. On the other hand, the positive long-term effect remains relatively close to the baseline, both on what concerns the magnitude and statistical significance. Finally, the relation between oLTV and the LGD in this setting remains in line with the baseline specification, despite the positive correlation between the two variables becoming statistically and economically significant at a higher level (it now starts at the 90% to 100% bucket, instead of the 80% to 90% bucket).

Table 4. Sensitivity analysis of the determinants of the LGD of mortgage loans

	Baseline	**Excluding banks with more than 30% of loans with an LTV =100%**	**Risk-free rate: German 10y treasury bonds**	**Risk-free rate: 2-y Euribor swap rate**
hpa_{t-1}	-0.337***	-0.202***	-0.033	-0.039**
	(0.073)	(0.017)	(0.017)	(0.015)
hpa_{t-4}	-0.018	-0.000	0.032**	0.030*
	(0.010)	(0.008)	(0.012)	(0.012)
hpa_{t-8}	0.003	0.009	-0.044***	-0.027**
	(0.015)	(0.013)	(0.011)	(0.009)
hpa_{t-12}	-0.005	0.001	-0.045*	-0.034*
	(0.015)	(0.016)	(0.020)	(0.017)
hpa_{t-16}	0.077**	0.032*	0.112**	0.098**
	(0.028)	(0.012)	(0.035)	(0.032)
hpa_{t-20}	0.295***	0.114***	0.167**	0.159**
	(0.074)	(0.012)	(0.054)	(0.049)
hpa_{t-24}	0.227**	0.089***	0.187**	0.167**
	(0.079)	(0.023)	(0.061)	(0.057)
D2(50%<oLTV≤70%)	-0.008***	-0.005***	-0.007***	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)
D3(70%<oLTV≤80%)	-0.007*	0.000	-0.0135***	-0.0131***
	(0.003)	(0.002)	(0.003)	(0.002)
D4(80%<oLTV≤90%)	0.031***	0.037***	0.006	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
D5(90%<oLTV<100%)	0.091***	0.095***	0.049***	0.039***
	(0.004)	(0.003)	(0.005)	(0.004)
D6(oLTV=100%)	0.119***	0.098***	0.079***	0.067***
	(0.006)	(0.013)	(0.007)	(0.006)
D7(100%<oLTV≤110%)	0.144***	0.117***	0.100***	0.087***
	(0.012)	(0.015)	(0.013)	(0.012)
D8(110%<oLTV≤120%)	0.196***	0.173***	0.157***	0.145***
	(0.010)	(0.019)	(0.010)	(0.009)
D9(120%<oLTV≤150%)	0.316***	0.296***	0.278***	0.264***
	(0.013)	(0.009)	(0.016)	(0.016)
D10(oLTV>150%)	0.626***	0.527***	0.603***	0.597***
	(0.039)	(0.023)	(0.041)	(0.042)
Loan, borrower and macro controls (excluding LTV)	YES	YES	YES	YES
Bank FEs	YES	YES	YES	YES
Region FEs	YES	YES	YES	YES
Observations	12,692	7,631	12,692	12,692
adj. R-sq	0.6872	0.630	0.695	0.706
AIC	-31,174.5	-24,298.0	-35,242.5	-36,973.7
BIC	-30,980.8	-24,117.6	-35,048.8	-36,780.1

Source: Author's calculations. | Notes: For the oLTV dummy variables, the coefficients represent the discrete change from the base category (loans with an oLTV<50%). The standard errors are clustered at the bank-level. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively. Time period 2009-2019.

Overall, and despite some differences in terms of magnitude and statistical significance of the coefficients, the sensitivity analysis performed seems to corroborate the conclusions obtained in the previous section.

6.2. Sensitivity analysis to the threshold regression

In this subsection we re-estimate the threshold regressions to evaluate if and how the discontinuity thresholds are affected by the sensitivity analysis conducted.

Results reported in Table 5 are close to the ones obtained in our baseline specification. The thresholds for the discontinuity in the relationship between the oLTV ratio and the LGD of mortgage loans stand at a range between 85% and 100%. Thus, overall, the sensitivity analysis results seem to confirm that the critical area in the relationship between LGD and LTV ratio lies between 80% and 100%.

Table 5. Sensitivity analysis for the discontinuity values in the relationship between the LTV ratio and LGD of mortgage loans

Order	Baseline	Excluding banks with more than 30% of loans with an LTV=100%	Risk-free rate: German 10y treasury bonds	Risk-free rate: two-year Euribor swap rate
		Only constant (%)		
1	93	88	100	100
2	100	94	99	99
		Constant and explanatory variables (%)		
1	94	88	100	100
2	100	95	85	90

Source: Author's calculations. | Notes: The baseline threshold regression is based on the specification presented in column 3 of Table 2.

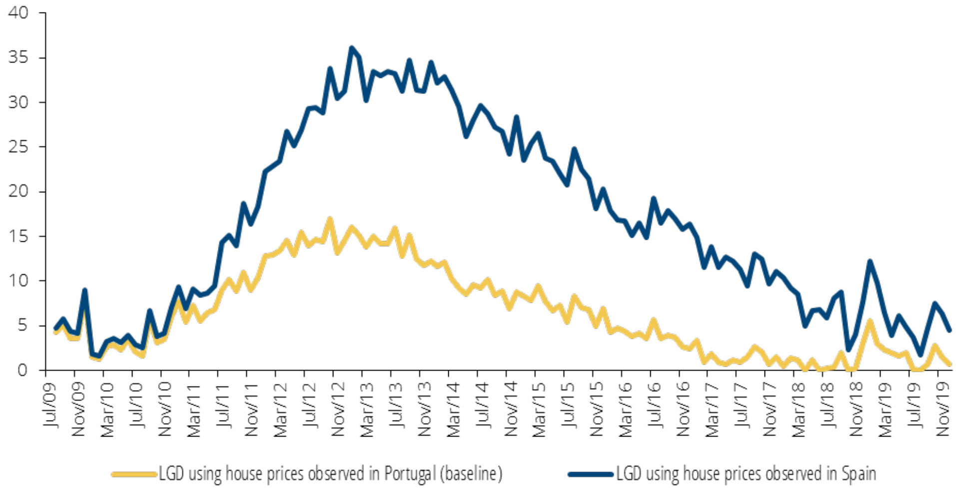
7. Simulation Analysis

Before the GFC, real house prices in Portugal recorded mostly negative annual growth. In the aftermath of the GFC and especially of the sovereign debt crisis, Portugal experienced house price declines and only at the end of our sample period prices recorded a more buoyant growth (Figure 1). Thus, Portugal did not experience a housing bubble prior to the onset of the GFC like Spain or the United States. Since the main purpose of our paper is to analyze how housing cycles influence LGD of mortgage loans, in this section we test the impact of a housing market bubble on our results. In order to do that, and as a simulation exercise, we redo all our estimates by replacing the evolution of housing prices observed in Portugal with those recorded in Spain during the same period, i.e. assuming Portugal recorded a housing bubble before the GFC.

Table A2 presents the summary statistics of our sensitivity analysis dataset. The impact of replacing the house prices in our sample is two-fold. First, it will affect, our dependent variable, the LGD of mortgage loans, since the collateral value will be updated according to a different house price pattern. Second, it will affect the annualized house price growth, the explanatory variable we use to proxy for the housing cycle. All the other loan, borrower and macro variables remain unchanged.

Assuming the Spanish house prices increases the average LGD by 13 p.p. (from 8% to 21%). The range of LGD variation is also more pronounced, compared with the baseline scenario, increasing from around 5%, in 2009, to almost 35% during the sovereign debt crisis, and then returning to levels of around 5% by the end of the sample period (Figure 2).

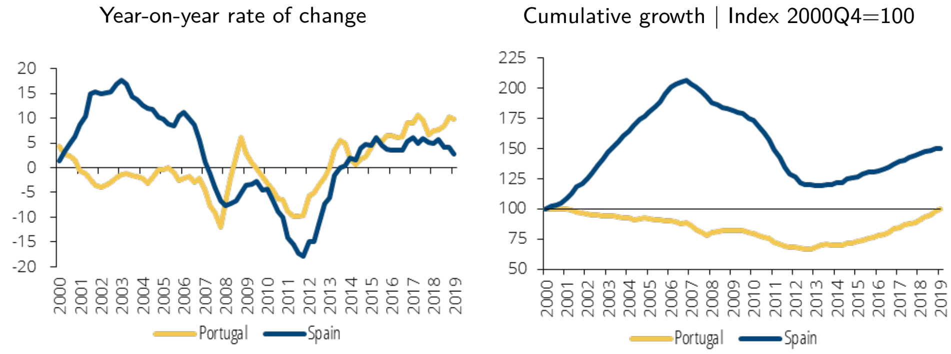
Figure 2: Loss given default, estimated with the house prices observed in Portugal and in Spain



Source: Author's calculations.

The LGD evolution is largely explained by the behavior of housing prices in Spain from 2008 onwards. Before the GFC, house prices in Spain consistently and significantly outperformed the evolution of house prices in Portugal. Between the end of 2000 and the end of 2007, real house prices in Spain more than doubled, while in Portugal they fell by about 14%. However, since the end of 2008, a mean-reversion pattern can be observed, as house prices in Portugal fell less during the sovereign debt crisis and grew at a higher rate thereafter (Figure 3).

Figure 3: Real house prices in Portugal and Spain



Source: Organization for Economic Co-operation and Development (OECD) (author's calculations). | Notes: The last observation refers to 2019 Q4. House prices are seasonally adjusted. Real house prices are obtained from nominal house prices deflated using the private consumption deflator from the national account statistics.

7.1. The drivers of the LGD of residential mortgage loans

Table 6 reports the results of regression (3) when we replace the evolution of housing prices observed in Portugal by those recorded in Spain. Results largely resemble those of the baseline regression. We continue to observe a distinct short and long-term effects of the house price cycle on the LGD of mortgage loans, although the positive long-term effect is now stronger. Estimated coefficients from the full specification in column 6, show that an increase in house prices one quarter prior to credit origination decreases LGD. On the other hand, an increase in house prices 4, 16, 20 and 24 quarters prior to credit origination, increases LGD. The coefficients associated with house prices 8 and 12 quarters prior to credit origination are not statistically significant. The strongest negative long-term effect is consistent with the harshest mean-reversion pattern of house prices when considering the Spanish house price dynamics, since in this case we observe a reversion of a housing bubble. When the housing prices are growing too fast and a bubble develops in the housing market, people buy houses at peak prices. In the long-term, the market tends to fall, which means the equity generated during housing bubbles may not be sustainable. On the other hand, in periods of relative house price stability or even after a significant drop in real estate prices, borrowers purchase houses at lower prices, which means the likelihood of prices going up is higher. In this case, borrowers generate equity in the property more steadily, as the short-run effect is more durable and the long-term correcting effect is less severe.

In this setting, a higher oLTV ratio continues to be associated with a higher LGD of mortgage loans, but now the threshold with statistical significance is lower than in our baseline specification, as it starts in 70% to 80% bucket (instead of the 80% to 90% bucket. This decrease is intuitive, since when there is more exuberance in real estate prices, the LTV ratio at which LGD becomes negative is lower. Column

6 of Table 6 show us that, compared with the base category (oLTV $\leq$ 50%) and assuming everything else constant, the LGD of a mortgage loan with an oLTV ratio between 70% and 80% is, on average, 7.7 p.p. higher, while the LGD of a loan with an oLTV ratio between 80% and 90% is 14 p.p. higher. If LGD is between 90% and 100%, equal to 100%, 100% $<$ oLTV $\leq$ 110%, 110% $<$ oLTV $\leq$ 120%, 120% $<$ oLTV $\leq$ 150%, and oLTV $>$ 150%, average LGD is 20.2 p.p., 23.9 p.p., 24.1 p.p., 29.3 p.p., 39.4 p.p., and 63.9 p.p. higher, respectively.

As expected, when we include a house price bubble in the equation, the explanatory power of house price history increases at the expense of the oLTV ratio. The explanatory power of house price history and loan characteristics (other than oLTV) increased by 18.3 p.p. and 9.2 p.p., respectively, to around 21.7% and 15.5%. Nevertheless, the oLTV ratio remains the most important determinant of LGD, explaining 62% of the total variation (89.7% in our baseline specification) (Table A3). Thus, our sensitivity analysis shows us that when we include a house price bubble in the analysis our main results remain.

Table 6. Simulation analysis: Regression of LGD on housing market cycle, loan and borrower characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
hpa_{t-1}	-0.176	-0.300*	-0.309*	-0.203**	-0.184**	-0.183**
	(0.147)	(0.146)	(0.126)	(0.063)	(0.067)	(0.066)
hpa_{t-4}	0.371**	0.370***	0.392***	0.392***	0.370***	0.351***
	(0.116)	(0.080)	(0.062)	(0.053)	(0.056)	(0.050)
hpa_{t-8}	0.199*	0.144	0.089	0.016	-0.008	-0.024
	(0.095)	(0.077)	(0.050)	(0.033)	(0.031)	(0.032)
hpa_{t-12}	-0.109*	-0.089	-0.072	0.022	0.018	0.012
	(0.046)	(0.062)	(0.060)	(0.042)	(0.043)	(0.041)
hpa_{t-16}	0.607***	0.486***	0.454***	0.362***	0.338***	0.330***
	(0.089)	(0.089)	(0.089)	(0.067)	(0.064)	(0.059)
hpa_{t-20}	0.395***	0.379***	0.385***	0.467***	0.499***	0.497***
	(0.093)	(0.068)	(0.058)	(0.079)	(0.083)	(0.082)
hpa_{t-24}	0.275***	0.228***	0.223***	0.123***	0.145***	0.162***
	(0.055)	(0.035)	(0.041)	(0.022)	(0.019)	(0.015)
oLTV (level)			0.001***			
			(0.000)			
D2(50%<oLTV≤70%)				0.008	0.007	0.008
				(0.014)	(0.013)	(0.013)
D3(70%<oLTV≤80%)				0.078***	0.076***	0.077***
				(0.020)	(0.018)	(0.018)
D4(80%<oLTV≤90%)				0.144***	0.140***	0.140***
				(0.022)	(0.018)	(0.018)
D5(90%<oLTV<100%)				0.209***	0.201***	0.202***
				(0.022)	(0.018)	(0.018)
D6 (oLTV=100%)				0.255***	0.238***	0.239***
				(0.016)	(0.015)	(0.015)
D7(100%<oLTV≤110%)				0.250***	0.241***	0.241***
				(0.029)	(0.029)	(0.029)
D8(110%<oLTV≤120%)				0.302***	0.292***	0.293***
				(0.024)	(0.022)	(0.022)
D9(120%<oLTV≤150%)				0.405***	0.393***	0.394***
				(0.018)	(0.015)	(0.014)
D10(oLTV>150%)				0.647***	0.640***	0.639***
				(0.033)	(0.031)	(0.031)
Loan, borrower and macro controls (excluding LTV)	NO	YES	YES	YES	YES	YES
Bank FEs	NO	NO	NO	NO	YES	YES
Region FEs	NO	NO	NO	NO	NO	YES
Observations	12,766	12,702	12,702	12,702	12,692	12,692
adj. R-sq	0.195	0.324	0.417	0.669	0.676	0.676
AIC	-8,313.9	-10,461.3	-12,338.4	-19,530.5	-19,869.8	-19,894.2
BIC	-8,261.8	-10,334.7	-12,204.3	-19,336.8	-19,676.2	-19,700.5

Notes: This table reports the results of regression (3) when we replace the evolution of housing prices observed in Portugal by those recorded in Spain. For the oLTV dummy variables, the coefficients represent the discrete change from the base category (loans with an oLTV<50%). The standard errors are clustered at the bank-level. ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively. Time period 2009-2019.

7.2. Threshold regression

In the previous subsection, we documented that the relation between LGD and oLTV is not linear and results obtained in this section so far seem to suggest the breakpoint dropped when we introduce a housing bubble in the house price history. In this subsection we re-estimate the threshold regression in order to evaluate if and how the thresholds are affected. Overall, results reported in Table 7 are close but slightly below those obtained in our baseline specification. The thresholds for the oLTV ratio that best fits the data are 86% and 90%, when only the constant vary and when all the coefficients are allowed to change, respectively. When we allow for a second threshold, the results suggest 76%, when only the constant varies, and 69%, when all the coefficients change. These estimations confirm that the critical area in the relationship between LGD and LTV ratio has shifted slighly downwards, lying now in a range between 70% and 90%, very close to the critical area of our baseline specification.

Table 7. Simulation analysis: Threshold regression results for the discontinuity values in the relationship between the LTV ratio and LGD of mortgage loans

Only constant		Constant and explanatory variables	
Order	LTV ratio estimated threshold (%)	Order	LTV ratio estimated threshold (%)
1	86	1	90
2	76	2	69

Source: Author's calculations. | Notes: The threshold regression in based on the specification presented in column 3 of Table 6.

8. Conclusions

Using loan-level data from the Portuguese Central Credit Register, this paper investigates the drivers of the LGD of residential mortgage loans in Portugal. We find that the oLTV ratio is the most important determinant of the LGD of mortgage loans, although the relation between these two variables is not linear. A higher oLTV ratio is associated with a higher LGD of mortgage loans, but only above a certain threshold. We provide evidence that the critical area in the relationship between these two variables lie in a range between 80% and 100%.

The housing cycle history prior to credit origination also plays a relevant role, particularly if there is a significant house price appreciation, with distinct short and long-term effects. A housing price appreciation just before loan origination reduces the future LGD, as a house price increase tends to have a positive short-term serial correlation. On the other hand, the long-term effect suggests that when housing cycles are endemic, the price appreciation may increase the LGD. In this scenario, the higher house price has increased in the past, the higher the future LGD is expected to be. Our results are aligned with research that shows that house prices exhibit serial correlation and mean reversion, where large market swings are usually followed by reversals to the unobserved fundamental price levels.

Our results provide some important insights in terms of policy. From a macroprudential perspective, they stress the importance of introducing borrower-based macroprudential measures, in particular limits on the LTV ratio, to reduce mortgage loans LGD. Our threshold regression results show that the critical area in the relationship between LGD and oLTV lies between 80% and 100%. On what concerns the microprudential regulation, the estimated LGD is one of the main inputs to estimate risk weights in the IRB approach, thus affecting the amount of regulatory capital required in percentage of risk weighted assets. Our results supports the use of a through-the-cycle LGD, given the mean reversion pattern of house prices towards an equilibrium level in the long run.

The literature on LGD determinants remains a topic where further research is much needed. Even without venturing into structural modelling, the avenues for reduced-form analysis are far from exhausted. For instance, it would be interesting to study how borrowers' income and wealth influence the LGD. Additionally, it would also be important to have data on the effective LGD, rather than an estimated LGD.

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Appendix

Threshold regression

To estimate the thresholds for the discontinuity in the relationship between the LTV ratio and the LGD of mortgage loans, we used the threshold estimation framework proposed by Hansen (2000). A simple two-regime threshold model based on our linear regression model, where only the constant of the model is allowed to vary according to the LTV ratio, can be represented as follows:

$$\begin{aligned} LGD_{i,t,t+k} = \alpha_1 \times I(oLTV_{i,t} \leq \gamma) + \alpha_2 \times I(oLTV_{i,t} > \gamma) + \\ \beta_1 \times hpa_{t-1} + B_2 \times hpa_{t-j} + B_3 \times X_{i,t} + B_4 \times Y_{r,t} + \\ \gamma_r + \delta_b + \varepsilon_{i,t} \end{aligned} \tag{4}$$

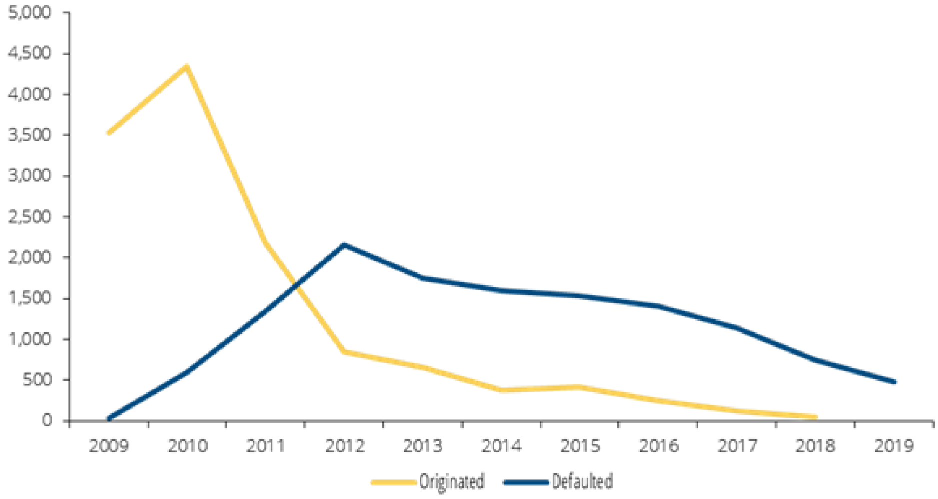
Where γ is the threshold to be estimated and I(.) is an indicator function that equals 1 if the condition between brackets is true and zero otherwise. For a loan with an LTV ratio below a certain value γ the constant is given by α_1, while for a loan with an LTV ratio above γ the constant is given by α_2. Besides the constant, threshold models also allow other coefficients of the model to vary according to different regimes. The sum of squared residuals function of the two-regime threshold model can be estimated as:

$$\begin{aligned} S(\beta, \gamma) = \sum_{i=1}^{N} (LGD_{i,t,t+k} - \alpha_1 \times I(oLTV_{i,t} \leq \gamma) - \alpha_2 \times I(oLTV_{i,t} > \gamma) - \\ \beta_1 \times hpa_{t-1} - B_2 \times hpa_{t-j} - B_3 \times X_{i,t} - B_4 \times Y_{r,t} - \gamma_r - \delta_b)^2 \end{aligned} \tag{5}$$

Since the regression is nonlinear and discontinuous, we cannot estimate the model parameters using the ordinary least squares (OLS). However, since the model is linear for a fixed value of γ with respect to the remaining parameters, the model parameters can be estimated using the conditional least squares (CLS). The CLS estimators $\hat{\beta}$ and $\hat{\gamma}$ correspond to the joint minimizer of $S(\beta, \gamma)$. Usually, in this approach, γ is bounded by the set $\Gamma = (\underline{\gamma}, \overline{\gamma})$, where $\underline{\gamma}$ and $\overline{\gamma}$ are the $\tau - th$ and $(1 - \tau) - th$ percentiles of the threshold variable, respectively, so that each regime has at least $N\tau$ observations. This procedure is intended to ensure that an adequate number of observations is used in the estimation of the parameters in each regime. The parameter τ is called the trimming parameter. We choose a trimming parameter of 0.1, which means that we exclude observations with a oLTV ratio below the 10th percentile or above the 90th when performing the grid-search procedure to select the thresholds.

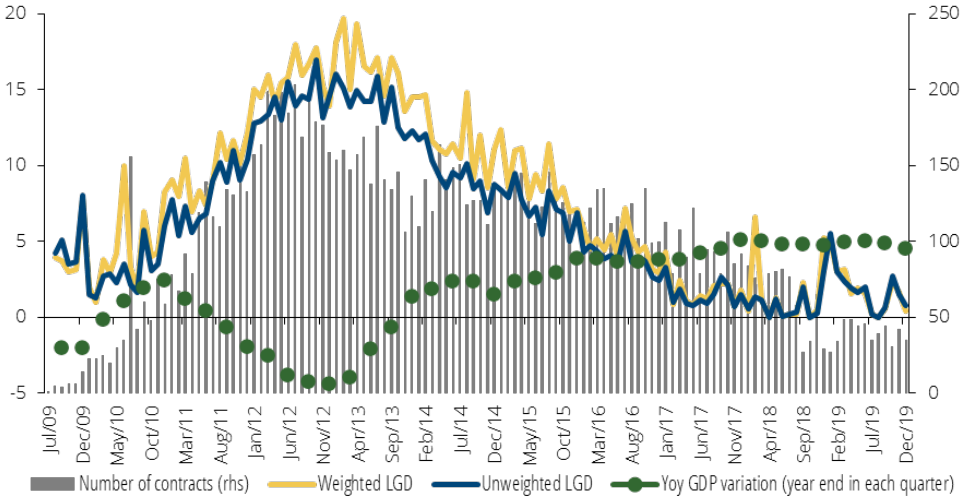
Figures and Tables

Figure A1: Number of contracts in the sample | By year the loan was granted and by the year it defaulted



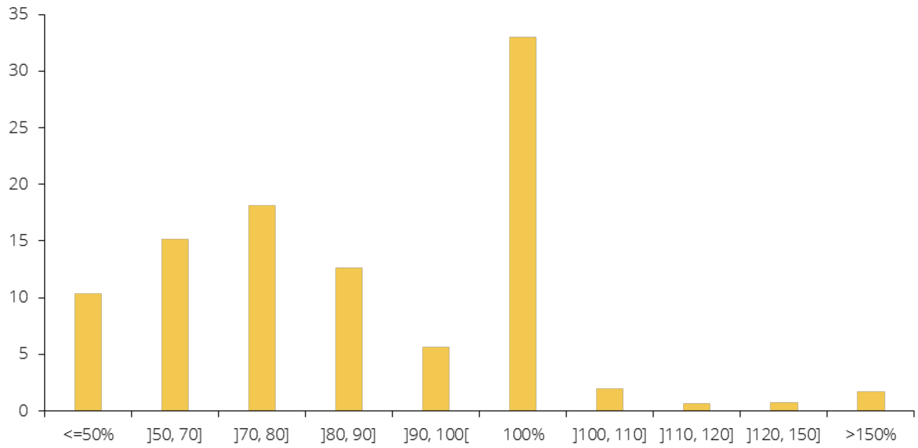
Source: Banco de Portugal (author's calculations).

Figure A2: Loss given default, number of defaulted contracts and GDP year-on-year rate of change



Source: Banco de Portugal and Statistics Portugal (author's calculations).

Figure A3: Distribution of the loans in the sample by class of oLTV ratio | In percentage



Source: Central Credit Register (author's calculations). | Notes: Time period between 2009 and 2019. The original loan-to-value ratio (oLTV) is the ratio between housing loan(s) and the value of the house granted as collateral.

Table A1. Definition of variables

Variable	Definition	Source
Borrower level data		
Age at contract origination	's age at contract origination (years).	Central Credit Register
Number of bank relations	Number of different bank relationships of the borrower. In cases where a debtor has several credit relationships with the same bank, only one relationship is considered.	Central Credit Register
Number of credit products	Number of different credit products of the borrower. In cases where a debtor has several credit products of the same type (e.g. two credits for house purchase), only one credit product is considered.	Central Credit Register
Loan level data		
LGD	Loss given default of residential mortgage loans, estimated according to the methodology presented in Section 2 (in percentage).	Central Credit Register
LTV ratio at origination	Ratio of the loan amount at contract origination to the appraisal value of the immovable property pledged as collateral (in percentage).	Central Credit Register
Amount at origination	Loan amount at contract origination (in euros).	Central Credit Register
Other guarantee (besides the house)	Binary variable which equals 1 if the loan has another guarantee besides the immovable property pledged as collateral and 0 otherwise.	Central Credit Register
Loan maturity	Loan original maturity (in years). Loan maturity is only available at the Central Credit Register by maturity buckets.	Central Credit Register
Macro data		
Regional GDP per capita (euros)	GDP per capita at the region (NUTS3) level (euros).	Statistics Portugal
Annual variation of GDP per capita	Year-on-year variation of the GDP per capita at the region (NUTS3) level.	Statistics Portugal
Real house price variation	Quarterly annualized real house price variation.	OECD

Table A2. Descriptive statistics: sensitivity analysis

	N	Mean	Std.Dev.	25th pct.	Median	75th pct.
LGD (%)	12,766	21	19	0	19	37
LTV ratio at origination (%)	12,777	87	97	70	84	100
Borrower age at contract origination (years)	12,720	41	11	33	40	48
Number of bank relations	12,777	2	2	1	2	3
Number of credit products	12,777	2	1	2	2	3
Share housing loans (%)	12,777	88	16	83	94	100
Loan amount at origination (euros)	12,777	83,192	83,451	38,400	67,193	104,871
Other guarantee (besides the house)	12,777	0.11	0.31	0	0	0
Loan maturity: $<=$ 10 years (dummy)	12,777	0.04	0.20	0	0	0
Loan maturity:]10 years, 20 years] (dummy)	12,777	0.15	0.35	0	0	0
Loan maturity:]20 years, 30 years] (dummy)	12,777	0.34	0.47	0	0	1
Loan maturity: $>$ 30 years (dummy)	12,777	0.47	0.50	0	0	1
Regional GDP per capita (euros)	12,713	17,424	4,574	14,233	15,774	23,485
Annual variation of GDP per capita (%)	12,713	-0.01	3.12	-2.27	-0.32	1.91
Real house price variation (%)	12,777	-5.72	6.18	-9.36	-3.16	-2.36

Table A3. Explanatory power, by variable category | PT and ES house prices

Variable	PT house prices	ES house prices	Percentage point difference
oLTV ratio	89.7%	62.0%	-27.7
Loan characteristics (other than oLTV ratio)	6.3%	15.5%	9.2
House price history	3.4%	21.7%	18.3
GDP	0.6%	0.8%	0.2

Source: Author's calculations. | Notes: The contributions are displayed as percentages of the overall R-squared. The R-squared decomposition is based on the results from column 6 of Table 2 (PT house prices) and Table 6 (ES house prices).

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