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Abstract

Booming house prices have been historically correlated with the loosening of banks' lending standards. Nonetheless, the evidence in Spain shows that the deterioration of lending policies may not be fully captured by the popular loan-to-value (LTV) ratio. Drawing on two large datasets comprising more than five million mortgage operations that cover the last financial cycle, we show that the LTV indicator may exhibit a misleading picture of actual mortgage credit imbalances and risk. In turn, risk identification improves when other metrics are considered. In particular, we show that loan-to-price (LTP) as well as ratios that consider the income of borrowers are major determinants of mortgage defaults. Moreover, we identify relevant non-linear effects of lending standards on default risk. Finally, we document that the relationship between lending standards and default rates changes over the cycle. Overall, the findings provide useful insights for the design of the macroprudential policy mix and, in particular, for the implementation of borrower-based measures.

Keywords: housing market, lending standards, defaults, macroprudential policy.

JEL classification: C25, E58, G01, G21, R30.

Resumen

Incrementos excesivos de los precios de la vivienda han estado históricamente correlacionados con el deterioro de los estándares crediticios de las hipotecas. No obstante, la evidencia en España muestra que la ratio préstamo-valor (LTV, por sus siglas en inglés) no refleja apropiadamente estos estándares. Utilizando dos extensas bases de datos que incluyen información de más de cinco millones de operaciones hipotecarias en España durante un período que cubre el pasado ciclo financiero, encontramos evidencia de que el indicador LTV presenta importantes limitaciones para el análisis de vulnerabilidades. Hallamos que la identificación de los riesgos mejora cuando se incluyen otros indicadores. En particular, reconocemos que la ratio préstamo-precio de transmisión (LTP, por sus siglas en inglés), así como ratios que incorporan el ingreso de los prestatarios, son determinantes muy relevantes de los impagos de hipotecas. Adicionalmente, identificamos importantes efectos no lineales de los estándares de crédito sobre el riesgo de impago. Por último, encontramos que la relación entre los estándares de crédito y la probabilidad de impago es dinámica y cambia a lo largo del ciclo financiero. En general, nuestros resultados proporcionan un mejor entendimiento de los efectos que puede tener la implementación de medidas macroprudenciales.

Palabras clave: mercado de la vivienda, estándares de crédito, riesgo de impago, política macroprudencial.

Códigos JEL: C25, E58, G01, G21, R30.

1 Introduction

The real estate sector has historically played a major role on previous systemic crises (Jordà *et al.*, 2016). In particular, a close relationship between imbalances in real estate prices and credit has been identified in several countries (Shüller *et al.*, 2015; Galati *et al.*, 2016; Rünstler and Vlekke, 2017).[1] Recent international evidence also shows a large deterioration of lending standards in countries that presented a boom of house prices and credit in the past (Kelly *et al.*, 2019, show evidence for European Union countries). Certainly, the correlation between the deterioration of lending standards and systemic crises is well documented in a number of cross-country studies (Lim *et al.*, 2011; Claessens *et al.*, 2012; Cerutti *et al.*, 2017).[2]

These findings have motivated authorities in many countries to actively use borrower-based measures to ensure sound banks' lending policies, especially after the last crisis. In general, these measures, which mainly consist of limiting the amount of credit mortgagors can borrow, appear to be very effective in containing house prices growth and mitigating the pro-cyclicality of credit and leverage (Wong *et al.*, 2011; Claessens *et al.*, 2012; Kelly *et al.*, 2018). In this context, loan-to-value (LTV) limits seem to be the preferred policy tool. Indeed, by 2013 half of countries of a large sample compiled by the International Monetary Fund (IMF) had implemented caps on LTV (IMF, 2013).[3] More recently, the European Systemic Risk Board (ESRB) reports that 18 countries in the EU have implemented LTV caps since 2013 (ESRB, 2018).

Nonetheless, policy circumvention might impair the effectiveness of policy tools such as LTV limits. The reason is that banks may circumvent regulation through different mechanisms, such as increasing consumption credit, loosening other lending standards, or re-allocating their portfolios towards borrowers with a riskier profile. These types of unintended consequences have been recently documented in Canada, Israel, Turkey, and Ireland (see IMF, 2013; Baziki and Çapaciouglu, 2018; Tzu-Ilan, 2017; Acharya *et al.*, 2019; respectively).

In Spain, some restrictions to issue covered bonds shed light on another interesting mechanism to by-pass LTV constraints (Duca *et al.*, 2010). To issue these securities, Spanish banks need to maintain eligible collateral, i.e. mortgages that meet certain characteristics. Mainly, mortgages with LTV above 80% are excluded from the eligible collateral pool (see IMF, 2006, for more details on this regulation). As a consequence, before the crisis and in a context of rapid credit growth banks had incentives to grant loans with too optimistic or *inflated* appraisals as a means to increase the stock of eligible loans and raise secured funding. The existing evidence shows that the presence of inflated valuations in mortgages collateral was certainly important in Spain (see, Bover *et al.*, 2019; Montalvo and Raya, 2018). This confirms that policy implementation should not rely on a single measure, like LTV limits. Likewise, it suggests that the assessment of lending standards should not depend exclusively on the LTV ratio, as it may provide an incomplete picture of vulnerabilities in certain cases.

1 In Spain, this relationship has been very strong. Systemic crises in Spain have been preceded by periods of rapid growth of house prices, mortgage credit and credit to construction firms and real estate developers (Estrada and Saurina, 2016).

2 Other studies have also confirmed the connection between lending standards and the probability of default of mortgages (May and Tudela, 2005; Aron and Muellbauer, 2016; Lazarov and Hinterschweiger, 2018).

3 Cerutti *et al.* (2017) extend the sample to 119 different countries finding that caps on LTV ratios are used in 21% of the sample.

Against this background, our contribution to the literature is threefold. First, we analyze to what extent the LTV ratio might mask mortgage credit imbalances when collateral valuations are biased, and whether or not other lending standards indicators might be helpful to improve risk identification. While the presence of optimistic valuations in mortgages collateral has already been covered in the literature (Agarwal *et al.* 2019; Ben-David, 2011), the link between *inflated* appraisals and defaults remains largely unexplored.[4] The implications of this relationship has been recently raised as a concern among national authorities implementing borrower-based measures.[5]

Second, we explore non-linear effects of lending standards at origination on default risk. Non-linearities in this context have been very little explored and the few studies addressing these issues have either used small samples or focused on specific subgroups of mortgages such as those categorized as subprime or those for buy-to-let purposes (May and Tudela, 2005; Haughwout et al, 2008; Kelly and O'Toole, 2018).

Third, we assess the relationship between lending standards and risk over the cycle. Recent studies have identified differential effects of borrower-based measures on credit and prices during booms and busts (Claessens *et al.*, 2012; Cerutti *et al.*, 2017; Poghosyan, 2019). In this context, we contribute to this literature by approaching this analysis from a micro perspective and exploring the link between banks' lending policies and risk.

For these purposes, we take advantage of two large datasets at loan-level, containing information on mortgage and borrower characteristics of more than five million credit operations granted in Spain over a long-time span, starting well before the crisis. Our results confirm that the LTV indicator may distort the identification of imbalances in the mortgage market in the presence of regulation linked to this ratio. In this context, we find that the loan-to-price (LTP) ratio does a better job in terms of risk identification. We also evidence the usefulness of considering a bunch of indicators to capture the multidimensionality of lending standards and to identify properly the relationship between mortgage characteristics and risk.

Moreover, we identify important non-linear effects of LTV, LTP and maturity on default risk and relevant interactions between them and income-related measures. Our findings indicate that combining different dimensions of lending standards is key when implementing borrower-based measures, as well as to get the full picture of the impact of lending standards on default risk. While our results hold when controlling for the effects of the financial crisis, we identify that this relationship is dynamic over the cycle. In particular, the LTV ratio becomes a poorer predictor of defaults following the crisis, while indicators linked to borrowers' repayment capacity, like the loan service-to-income ratio (LSTI), appear to become more relevant to explain defaults in post-crisis years. Overall, our findings provide useful insights for policy makers in the implementation of borrower-based measures.

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4 Ben-David (2011) evidences that before the financial crisis financially constrained borrowers in the United States inflated transaction prices to draw larger mortgages. Raya (2018) is the only previous attempt to study this relationship in Spain. However, the author uses a very short sample of 300 loans from a real estate company and granted by just one specific bank.

5 The central bank of The Netherlands has raised concerns on the effectiveness of an already in place LTV cap due to the presence of distortions in appraisals (De Nederlandsche Bank, 2019). Also, in Portugal the central bank has introduced a recommendation to limit the LTV ratio of new loans. The recommendation accounts for the potential differences between appraisals and transaction prices (Leal and Lima, 2018).

The document comprises seven sections besides this introduction. Section 2 provides an overview of the existing literature on the effectiveness of borrower-based measures, the determinants of mortgage default risk, and policy implementation. Section 3 describes the datasets employed in the analysis. Section 4 presents the evolution of lending standards and defaults in Spain during the period under study. Section 5 describes the model used. Section 6 presents the main results and some guidance for policy implementation. A set of robustness exercises and extensions is presented in section 7. Finally, section 8 concludes the paper.

2 Literature review

Literature on lending standards of residential loans can be classified into three types of studies: effectiveness of borrower-based measures, determinants of mortgages default and policy implementation. Regarding the effectiveness of borrower-based measures, most of this literature relies on the use of cross-country studies at macro-level identifying the effects of these policies on house prices, the credit cycle and financial stability. In this regard, Lim *et al.* (2011) have identified LTV and debt-to-income (DTI) limits to be effective in mitigating pro-cyclicality of credit and leverage using aggregate country-level data from 49 countries over 10 years. Wong *et al.* (2011) have also found LTV policies to reduce mortgage delinquency ratios and to have a positive impact on reducing cyclical systemic risk after examining these policies in 13 countries. Zhang and Zoli (2016) notice that housing-related policies have been successful on restraining house prices, credit and leverage in emerging economies and, in particular, in Asian countries. Carreras *et al.* (2018) find LTV and DTI limits to be very effective as well after analyzing a sample of 19 OECD countries under a cointegration-based analysis. More recently, Morgan *et al.* (2019) show the effectiveness of LTV caps on constraining mortgage credit after analyzing 4,000 banks from 46 countries. The benefits of LTV caps have also been examined theoretically through dynamic stochastic general equilibrium (DSGE) models. These studies have identified welfare improvement, reduction in household indebtedness and house prices curbing (Crowe et al, 2013; Rubio and Carrasco-Gallego, 2016).

As to the literature on the determinants of mortgages defaults, the first wave of these studies identified probabilities of default through option pricing theoretical models. In these models, a household chooses to default when the property value drops below the loan value minus a margin (Kau *et al.*, 1993; Deng *et al.*, 2003). Thus, these theories attribute defaults to negative equity while borrowers' characteristics are usually excluded. Departing from the seminal work by Vandell (1995), however, both negative equity and cash flow problems act as a double trigger (Foote *et al.*, 2008; Campbell and Cocco, 2015; Fuster and Willen, 2017). Guiso *et al.* (2013) further argue that besides net equity and cash flow, mortgage conditions are key to explain defaults. On this regard, a third strand of models considers loans quality, in addition to equity and cash flow issues, to explain arrears and repossessions.

At the empirical level most of the studies focus on the mortgage markets of the United States (US) and the United Kingdom (UK) due to the availability of micro-data at loan- and borrower-level. Quercia and Stegman (1992) and more recently Jones and Sirmans (2016) provide good reviews of this literature. In other countries empirical studies mainly rely on aggregated data (see Aron and Muellbauer, 2016, for a literature overview of these studies)[6]. At micro level, usually logit, probit and hazard models have been applied. Logit and probit models typically assess probabilities of default of mortgages depending on LTV and borrower and lender characteristics (Burrows, 1998; Lazarov and Hinterschweiger, 2018). In particular, income-related characteristics of the borrower have been found to be more important than equity factors, such as the LTV ratio, in determining defaults (Böheim and Taylor, 2000; May and Tudela, 2005). This finding has been also confirmed in models assessing time-to-default through hazard models (Lambrecht *et al.*, 1997; Lambrecht *et al.*, 2003).

6 At macro level, Engle-Granger two step methods (Brookes *et al.*, 1994), error correction models (Whitley *et al.*, 2004), vector autoregressive models (Figueira *et al.*, 2005), and simultaneous dynamic equation models (Aron and Muellbauer, 2016) have been proposed. These studies usually model aggregated unemployment rates and debt service ratios as measures of cash flow, and LTV and LTI as credit quality measures.

A third branch of these studies has focused more on the implications of borrower-based measures. Some studies have identified that the timing of activation of these policies is important. By combining macro- and micro-level data across countries, Claessens *et al.* (2012) and Cerutti *et al.* (2017) have evidenced that borrower-based measures are more effective during booms than in bust periods. Nonetheless, recently Poghosyan (2019) shows that during expansions the full effects of these tools are only reached after three years, while effects are more immediate and larger during downturns, when instruments are deactivated.

Recently, some studies have also explored the unintended consequences of borrower-based measures, concluding in favor of placing simultaneously policies linked to borrowers' income or mortgage terms besides the typical LTV limit. Baziki and Capacloglu (2018) find evidence on credit spillovers from a LTV cap measure in Turkey, which led to a significant increase in consumption credit. Tzur-Ilan (2017) also shows an increase in unsecured credit, higher interest rates and longer maturities following the introduction of an LTV measure in Israel. After analyzing the implementation of LTV and loan-to-income (LTI) caps in Ireland, Acharya *et al.* (2019) identify that these measures had a direct effect on stabilizing house prices, but they led to a re-allocation of new mortgages towards riskier borrowers. Thus, side effects of these policies have to be carefully considered, in particular due to regulatory arbitrage, leakages and spillovers.

Other type of policy studies has analyzed the calibration of borrower-based instruments by modeling non-linearities of lending standards that allow identifying key thresholds. Haughwout *et al.* (2008) find non-linear effects of LTV and DTI in default rates of mortgages in the US during the first year of life of the loan. Qi and Yang (2009) find non-linearities of the LTV ratio in explaining the loss given default of mortgages in the US. In an application to the UK, May and Tudela (2005) find important differences in default rates of mortgages for various levels of LTV and interest coverage ratio, which may be informative from a policy perspective. Kelly *et al.* (2018) obtain relevant thresholds of LTV and LTI in Ireland. The authors also identify that placing simultaneously both measures is more effective in curbing house prices growth than using only one measure. More recently, Kelly and O'Toole (2018) apply a non-linear spline model to a sample of buy-to-let mortgages in the UK. The authors identify important non-linear effects of LTV and debt service-to-income (DSTI) at origination.[7]

In the case of Spain, very few studies have analyzed lending standards. Akin *et al.* (2014) analyze the determinants of LTV and spreads at loan-level over the period 2005-2010, using data from a housing market intermediary. They find too-soft lending standards and excessive risk-taking during the boom period, particularly from banks with poor corporate governance. They also evidence the use of "over-appraising" as a mechanism to circumvent LTV regulation. In particular, the authors argue that Spanish banks encouraged appraisal firms to artificially over-appraise properties and lower LTV. In turn, low-LTV loans allowed banks to, among other, enlarge the number of safer, eligible mortgages for issuing covered bonds (see Duca *et al.*, 2010, for similar arguments).

Montalvo and Raya (2018) also study the over-appraisal mechanism in Spain. The authors state that this practice was intended to by-pass LTV constraints and that it had real effects, as it led to an intensification of the feedback loop between credit and house prices. In particular, they show that mortgages on properties with a high over-appraisal were mostly

7 DTI and DSTI are similar to LTI and LSTI. The former measures usually take on board all outstanding balances of mortgagors, while the latter might refer to mortgage debt exclusively.

granted to riskier borrowers. In this context, indicators relating loan values to market prices can be more indicative of the likelihood of delinquency than the traditional LTV. Recently, Bover *et al.* (2019) analyze a large loan-level database from Spanish land registries and confirm that over-appraisal increased importantly during the housing boom. Overall, biases in appraisals appear to be important in other jurisdictions, while the link with default rates has been less explored (Agarwal *et al.* 2019; Ben-David, 2011).

3 Data description

3.1 Spanish Association of Property Registrars –Colegio de Registradores (CdR)–

Our main data source is the Spanish Association of Property Registrars –Colegio de Registradores (CdR)–. The CdR offers loan-by-loan coverage for the full population of residential mortgages registered at local land registries since 2004 (5.6 million in total).[8] It allows us to study a rich set of mortgages characteristics, such as the principal amount or the maturity of loans, together with elements associated with the collateral of these operations, i.e. dwellings, including their location, the appraisal value or the price per square meter. All collateral and mortgages characteristics refer to the moment of origination of the loan.

In 2013 the CdR started to collect banks' applications for initiating foreclosure processes in a separate dataset. We use these applications as a proxy for problematic/defaulted loans. In total, banks initiated 112,000 foreclosure requests since that date (previous requests are not observed). After compiling the defaults, we need to merge the resulting dataset with the original one, in which key data such as the LTV ratio is available. To do this, we use common variables in the two data sources, including the municipality where the collateral is located, the type of dwelling, the date the mortgage was signed and some other characteristics (principal amount, interest rate and maturity). In total, after the merge we get 52,000 failed loans.

Since failed loans before 2013 are not identified as such, one concern is whether this omission may confound the empirical analysis.[9] We note, however, that the number of failed loans omitted should actually represent a very low proportion of total mortgages.[10] In addition, the observed failed loans present very different characteristics (in terms of risk) from those of performing loans, as we will describe in section 4.B. Overall, while there are some limitations with regard to the dataset of defaults, we think that the data is valid for the purposes of our research.

3.2 European DataWarehouse (ED)

One shortcoming of the CdR database is that it does not provide data on borrowers, such as their income. It gives no indication on the bank that grants the mortgage, either. To address these limitations, we consider the ED as a complementary database.

The ED is a huge repository of data relative to asset-backed securities (ABS) issued by European banks. Information is reported by banks under the guidelines of the European Central Bank ABS loan-level initiative, which aims to increase transparency in the securitisations markets.[11] Particularly before the crisis, Spanish banks have been active issuers of residential mortgage-backed securities (RMBS), which are securitisations in which the collateral pool is made up of residential mortgages. This allows us to exploit mortgage-level data of around 2 million of operations since 1999.[12]

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8 We define residential mortgages as loans in which the borrower is a household and the collateral is a dwelling. This definition is aligned with the ESRB Recommendation 2016/14 on closing real estate data gaps.

9 We note that we are able to see failures of loans *originated before* 2013, provided that they *default after* that date. Indeed, the vast majority of our sample of failed mortgages is made up of these operations.

10 According to supervisory information (aggregated data), the peak in the non-performing loans ratio in Spain was 6.3%, much lower than the recorded in most portfolios. It is also important to remark that this definition of non-performing loans is broader than the default rate computed in our exercise, based on foreclosure requests.

11 For more details, see https://www.ecb.europa.eu/paym/coll/loanlevel/html/index.en.html.

12 Gaudêncio *et al.* (2019) also use this database to assess default rates in residential mortgages in multiple euro area countries, including Spain.

On top of some variables already covered by the CdR, the ED database includes borrowers' information at the origination of loans, including their income or their employment status. In addition, in the ED database banks directly report whether loans have defaulted or have ended up in a foreclosure process, which makes the identification of problematic loans easier.

Nonetheless, one potential concern with this database is adverse selection. Since investors in the securitisation market cannot screen loans in the same way as banks do (asymmetric information), banks can in theory select *bad loans* to make up the collateral pool of these securities. If this were the case, the empirical analysis using ED data would be subject to selection biases. In this regard, some authors argue that certain mechanisms could mitigate adverse selection incentives, or even eliminate them. For instance, banks might retain part of the equity tranche of securitisations for signaling purposes or to build a good reputation in the markets. In an empirical application, Albertazzi *et al.* (2015) find that in the Italian RMBS market, whose institutional setting has some similarities with the Spanish one, securitised loans have a lower default probability than non-securitised credit. We cover this issue further below in section 7.3.

Overall, both databases offer a rich set of information that can be exploited to gain insights on the relationship between lending standards and risk.

3.3 Lending standards indicators

We turn now to define our set of lending standards indicators. Since the CdR database is more complete, we first try to collect these indicators from this database. If not possible, we use ED data exclusively.

Regarding lending standards linked to collateral value, we compute, using CdR data, the ratio of the principal amount of mortgages to: i) the appraisal value of the property (LTV), and ii) the price paid for the property (LTP), as follows:

$$\text{LTV ratio (\%)} = \frac{\text{Principal amount of the mortgage}}{\text{Appraisal value of the property}},$$

$$\text{LTP ratio (\%)} = \frac{\text{Principal amount of the mortgage}}{\text{Transaction price of the property}},$$

where the appraisal value is an estimation of the value (of the property) conducted by an appraisal company, and the transaction price is the value reported in the notarial deed as the purchasing price of the dwelling. While both appraisals and transaction prices reflect the underlying value of the collateral, they do not necessarily coincide. Indeed, as it will be described shortly, transaction prices and appraisal values differ, sometimes substantially. To capture discrepancies between the two ratios, we also construct a metric of over-appraisal (OA) in the mortgage market, following Montalvo and Raya (2018). This is the ratio between the appraisal value of the dwelling and its transaction price.

It is important to remark that in order to compute LTP and OA we need to merge two different datasets from the CdR. The first one contains information on the characteristics of mortgages (principal amount, appraisal), and the second one contains information on the purchasing price of dwellings. To do this, we follow the strategy in Bover *et al.* (2019) by selecting loan variables that are common in the two databases.[13] In this way, we are able to find the LTP ratio (and OA) for 1.3 million mortgages. Although this may potentially introduce a selection bias issue, we confirm that this procedure does not affect the results in the empirical analysis through a robustness exercise (see section 7.2).

Finally, we study the mortgage term, measured in years, and compute two indicators that account for borrowers' income (LSTI and LTI) as follows:

$$\text{LSTI ratio (\%)} = \frac{\text{Debt service during the first year of the mortgage}}{\text{Annual gross income of the primary borrower}},$$

$$\text{LTI ratio (\%)} = \frac{\text{Principal amount of the mortgage}}{\text{Annual gross income of the primary borrower}}.$$

The LSTI indicator is an estimation of the debt service expected to be paid during the first year of the mortgage contract against the gross annual income of the primary borrower (for details on the definitions, see Annex 1). In the LTI ratio, the numerator is the principal amount of the mortgage, while the denominator remains the same. Since the CdR does not collect mortgagors' income, we obtain this data from the ED repository. All indicators are calculated at the origination of the mortgage.

We present in Table 1 a summary statistics of these indicators along with other relevant characteristics of mortgages. Besides problematic loans, LTV and maturity also exhibit some differences between both databases. These differences and the potential implications for the analysis are explored in more detail in section 7.3.

13 "Common variables" include the type of dwelling, the location, or the usable floor area, as well as the cadastral references (available only for the most recent period). In the case of the ED, we cannot compute these indicators as there is no information on prices (denominator of the LTP and the OA ratios).

Table 1. Summary statistics by data source

Panel A. CdR dataset (2004-2017)

	Observations	mean	median	p10	p90	Std. Dev.
LTV	5,636,729	60.83	63.5	22.1	91.8	25.4
LTP	1,292,179	93.74	91.7	51.9	136.9	34.3
OA	1,272,419	1.37	1.26	0.98	1.98	0.43
Maturity (years)	5,632,645	25.40	28.0	12.0	35.0	9.2
Second-hand	5,636,729	0.62	1.0	0.0	1.0	0.5
Subsidised-housing	5,636,729	0.12	0.0	0.0	1.0	0.3
Problematic loans	5,636,729	0.01	0.0	0.0	0.0	0.1

Panel B. ED repository (1999-2017)

	Observations	mean	median	p10	p90	Std. Dev.
LTV	1,816,377	67.56	75.0	27.2	96.5	26.2
Maturity (years)	1,816,377	27.37	30.0	17.3	37.1	7.4
LTI	1,816,377	5.70	4.98	1.30	11.14	3.94
LSTI (%)	1,696,899	33.39	28.7	8.3	64.0	29.3
Employment status:						
Wage-earner	1,816,377	0.66	1.0	0.0	1.0	0.5
Civil servant	1,816,377	0.09	0.0	0.0	0.0	0.3
Unemployed	1,816,377	0.02	0.0	0.0	0.0	0.2
Self-employed	1,816,377	0.12	0.0	0.0	1.0	0.3
Other	1,816,377	0.11	0.0	0.0	1.0	0.3
Contract characteristics						
Remortgage	1,816,377	0.04	0.0	0.0	0.0	0.2
Non-RREcollateral	1,816,377	0.01	0.0	0.0	0.0	0.1
Second-home	1,816,377	0.01	0.0	0.0	0.0	0.1
Variable-rate	1,770,285	0.96	1.0	1.0	1.0	0.2
Problematic loans	1,816,377	0.04	0.0	0.0	0.0	0.2

Note: in Panel A, LTV is the loan-to-value ratio, LTP is the loan-to-price ratio (where price is the dwelling price as recorded in land registries), OA is the over-appraisal ratio, maturity is the duration of the mortgage at origination. Second-hand is a dummy equal to one if the mortgage collateral is a second-hand dwelling. Subsidised-housing is a dummy equal to one for government subsidised housing. In Panel B, LTI is the loan-to-income ratio, while LSTI is the loan service-to-income ratio. The remaining variables are categorical and equal to one when the condition is met. Employment status refers to the job position of the borrower (when the loan is originated), equal to one if the mortgagor pertains to the corresponding category. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other categories not included as wage earners, civil servants, unemployed or self-employed. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). Problematic loans are associated with banks´ applications for foreclosures in the CdR, and defaults declared by banks in the ED repository. This variable is equal to one whenever the loan has failed.

Source: Colegio de Registradores (CdR) and European DataWarehouse (ED).

4 An inspection of the relationship between lending standards and risk

4.1 The evolution of lending standards

In this section, we characterize the evolution of our lending standards indicators over time. For this purpose, we use the more comprehensive CdR database to describe LTV, LTP and maturities. In the case of LSTI and LTI the information comes from the ED repository as we cannot compute these indicators in the CdR.

In Figure 1.A we display the distribution of the LTV ratio, distinguishing between values above and below 80%. We observe that the share of high-LTV loans remains relatively unchanged over time, even during the run-up to the crisis. This outcome is striking given the large, cumulated imbalances during the booming period (Estrada and Saurina, 2016).

The behavior of appraisals, the principal amount of mortgages and the prices at which operations were registered (in land registries) provide some clues on this apparent puzzle (Figure 1.B). Before the crisis, appraisal values rose at similar rates than the principal amount of mortgages, leaving the LTV ratio almost unchanged. While transaction prices also augmented, they remained at much lower levels than appraisals in this period, resulting in much higher LTP (Figure 1.C). The result of these trends was the emergence of a substantial OA in the mortgage market: the difference between appraisal values and transaction prices was on average 37% between 2004 and 2007. The OA adjusted sharply during the crisis, coinciding with a strong drop in LTP, while LTV presented again a more muted trend. Given these results, LTP appears to describe much better the evolution of lending standards over the cycle.[14]

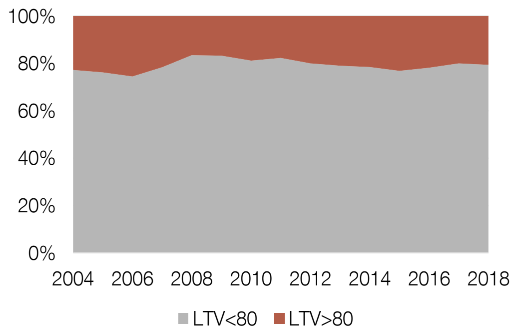
Regarding maturity, we show the evolution of mortgage payment terms at origination in Figure 1.D (the source is again the CdR). Similarly to LTP, we observe a cyclical pattern where mortgages with very long maturities, in particular those with terms above 35 years, increased importantly before the crisis and rapidly decreased afterwards. The extension of maturities in the former period could be the result of lending policies aimed at lowering the debt service of leveraged or liquidity constrained borrowers.

Finally, in Figures 1.E and 1.F we display the distribution of LSTI and LTI, respectively. These indicators have some advantages over collateral metrics, mainly because they are unrelated to third party valuations (appraisals), and seem to be more sensitive to shifts in the real estate cycle, as household income is more stable than house prices over the cycle (Leal and Lima, 2018). The evolution of both indicators is consistent with a substantial easing of credit standards during the expansion phase. In the years preceding the crisis, almost 70% of borrowers were dedicating more than 45% of their annual income to servicing debt and near 60% of new mortgages had a principal amount six times higher than the borrowers´ income. Contrary to LTV, these two ratios diminished rapidly following the financial crisis.

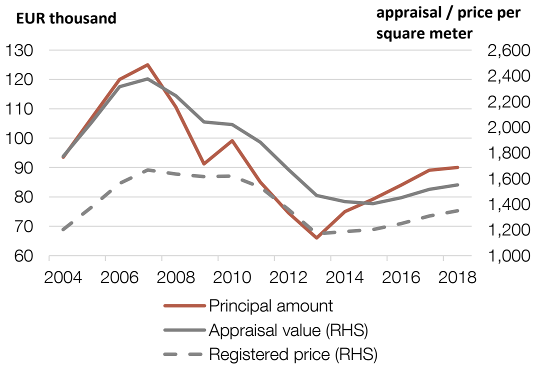
14 We do not address why appraisals were higher than dwelling prices during the booming period. Previous literature argues that regulation linked to LTV was behind this. In particular, LTV constraints to issue covered bonds (Duca *et al.*, 2010; Akin *et al.*, 2014), the higher risk-weights of high-LTV operations and reputational aspects (Montalvo and Raya, 2018) could explain the over-appraisal mechanism.

Figure 1. Lending standards. Evolution over time

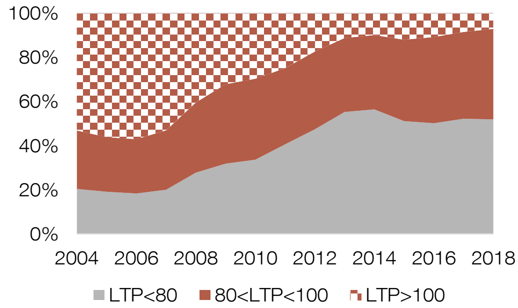
1.A. LTV ratio (%)



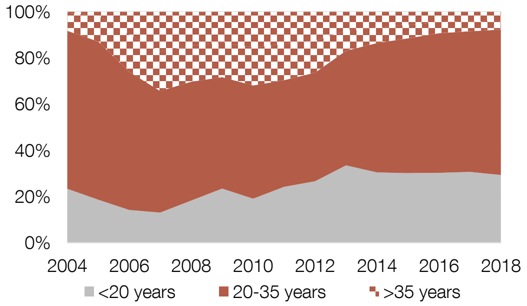
1.B. Principal amount, appraisal values and prices



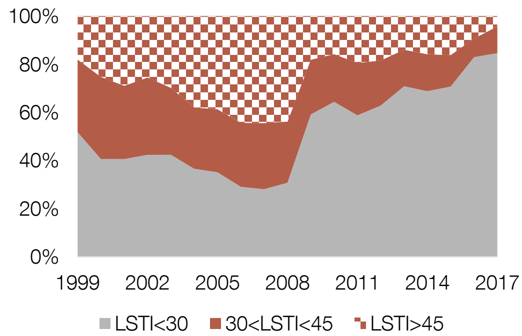
1.C. LTP ratio (%)



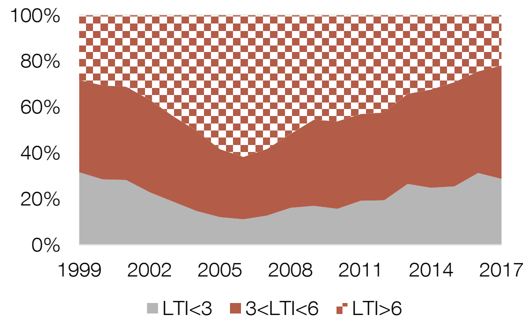
1.D. Maturity



1.E. LSTI ratio (%)



1.F. LTI ratio



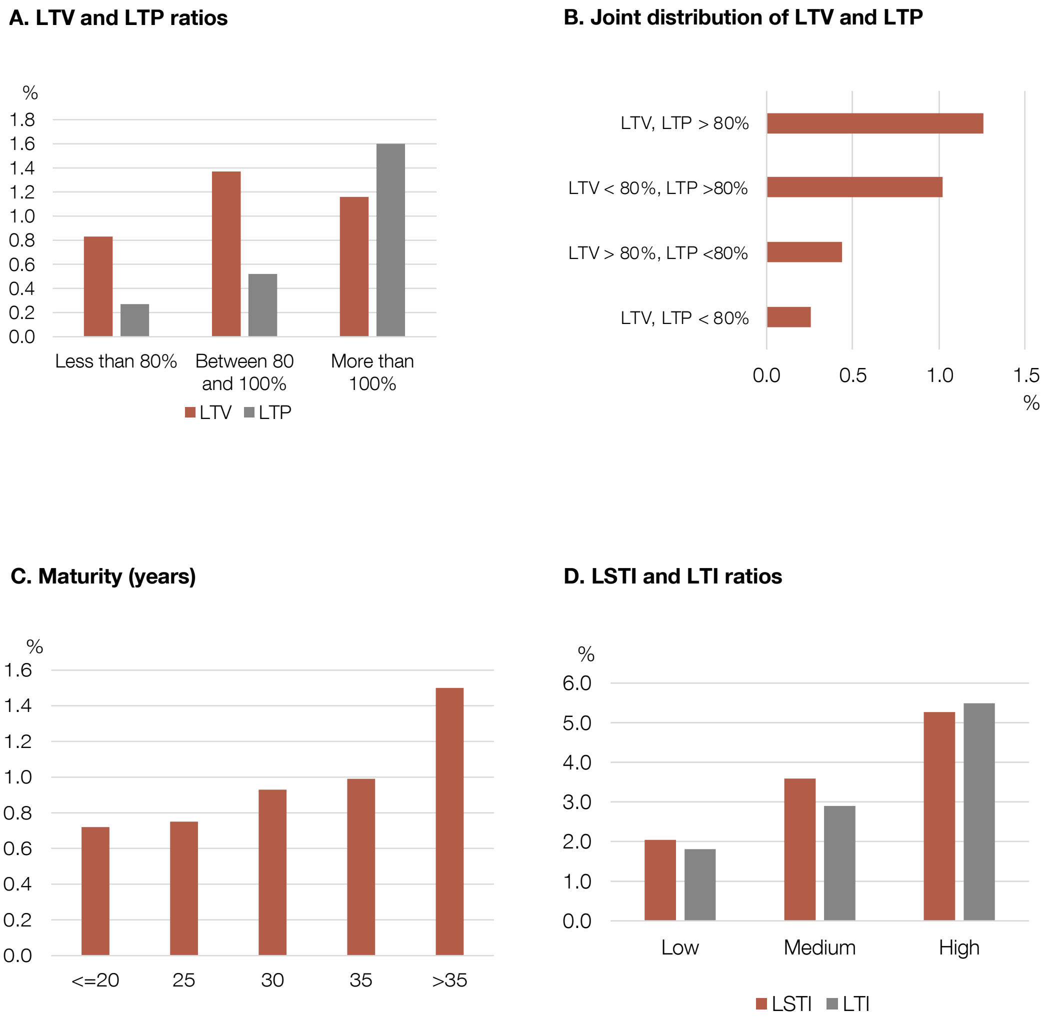
Note: LTV is the loan-to-appraisal value ratio; LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries; Maturity is the term of mortgages at origination; LSTI is the loan service-to-income ratio, where loan service refers to the first installment of new loans (principal amount plus interest payments); and LTI is the loan-to-income ratio. In figure 1.B, we use the median to characterize all variables (principal amounts, appraisals and prices).

Source: Colegio de Registradores (CdR) for Figures 1.A to 1.D, and European DataWarehouse (ED) for Figures 1.E and 1.F.

4.2 *Lending standards and default rates*

The previous analysis evidences that lending standards exhibit a cyclical pattern, as most of them deteriorated importantly before the crisis. This leads us to examine more closely the relationship between lending standards and default frequencies. In Figure 2, we show the share of failed loans in different sub-samples, defined according to low and high values of our lending standards metrics. Failed loans are represented either by the issuance of certificates of foreclosure (CdR) or by default records (ED).

Figure 2. Default rates of mortgages by lending standards at origination



Note: LTV is the loan-to-appraisal value ratio; LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries; Maturity is the term of mortgages at origination; LSTI is the loan service-to-income ratio, where loan service refers to the first installment of new loans (principal amount plus interest payments); and LTI is the loan-to-income ratio. Low-LSTI loans are loans with an LSTI ratio below 30%. Medium-LSTI loans cover loans with an LSTI ratio between 30-45%. High-LSTI mortgages are those above the latter percentage. Low-LTI refers to LTI below three times. Medium-LTI corresponds to LTI between three and six times, while high-LTI loans have LTI above six times.

Source: Own elaboration using data from the Colegio de Registradores (CdR) for figures 2.A to 2.C, and from the European DataWarehouse (ED) for figure 2.D.

Figure 2.A shows that loans with high LTV or LTP ratios yield higher historical default frequencies on average. Intuitively, high-leveraged operations are more vulnerable to price shocks, which would lead them to present negative equity with a higher probability (Vandell, 1995), and would limit their access to refinancing as well (Bilyk *et al.*, 2017).[15] In addition, borrowers who do not have enough savings to make a large down-payment might make up a substantial share of these loans. These mortgagors would have a lower financial cushion, and would be riskier as a result.

In the same figure, we show that the relationship with risk in the data is clearly non-linear. In particular, mortgages with high LTP (above 80%) present eight times higher default rates than those with a low ratio (below 80%). The increase is, however, fairly more modest for the LTV indicator. Indeed, above the 100% cutoff, there is no increase in the observed default rate. In Figure 2.B, we further illustrate the resulting default rates from the joint distribution of these indicators. As expected, mortgages with both low LTV and low LTP have lower default rates than other loans, while mortgages with both high LTV and high LTP are riskier. However, default rates remain at high levels in the segment of mortgages with low LTV and high LTP, while they are relatively low in the opposite situation. These results suggest that the relationship between the LTP ratio and defaults might be stronger than in the case of LTV. Thus, the former ratio not only describes better changes in lending standards, as pointed out previously, but might be also more reliable in terms of risk identification.

Regarding maturities, we observe that default rates tend to increase as maturity grows (Figure 2.C). In addition, we see a jump in default rates for payment terms over 35 years. This is interesting as it might imply that borrowers with longer term loans are more vulnerable to shocks (Campbell and Cocco, 2015).

Finally, in Figure 2.D we show the relationship between default rates and LSTI/LTI ratios, using the ED in this case. In principle, we would expect mortgagors of high LSTI/LTI loans to be more liquidity constrained and to be more vulnerable to income shocks, representing a higher risk (Fuster and Willen, 2017). This is indeed what we observe in Figure 2.D as mortgages with high LSTI/LTI values present a default frequency 2.5 times greater than that of mortgages with low values. In comparison with other indicators, the relationship between LSTI or LTI and default rates appears to be markedly more lineal.

15 Yet, Spanish mortgages are full-recourse loans. As a result, the role of negative equity on defaults might be much lower than in other jurisdictions.

5 Modelling lending standards and risk

The connection between lending standards and risk is studied through the identification of the effects of the former on the probability of default. For this purpose, we use a conditional logit model, where lending standards at origination and other characteristics of mortgages and borrowers are included as explanatory variables of the probability of default. This methodological approach has been used previously in micro studies exploring mortgages default determinants (see Aron and Muelbauer, 2016, for a review). The general specification is the following:

$$\log\frac{P(DM_i = 1|\boldsymbol{X}_i)}{P(DM_i = 0|\boldsymbol{X}_i)} = \alpha + \beta_1 LTV_i + \beta_2 LTP_i + \beta_3 Mat_i + \beta_4 LSTI_i$$

$$+\sum_{S=1}^{S} \psi_S Z_{is} + R_i + Y_i + B_i + \varepsilon_i$$

where i refers to mortgage operations; DM_i is a dummy equal to one for defaulted mortgages and zero otherwise; P represents the probability of a mortgage to go into default given certain determinants in matrix $\boldsymbol{X}_i$, which comprises a set of lending standards indicators, a set of S borrower, mortgage and collateral characteristics (in vector Z), and fixed effects for the region (province) of origination of the loan (R), the year of origination of the loan (Y) and the bank granting the mortgage (B). The specific variables included in the models depend on the dataset used. Table 2 below presents the variables available for the estimations under each of the datasets (CdR or ED), which are further defined in Annex 1.

Table 2. Variables included in the models by dataset

Category of variable	CdR	ED
Lending standards	LTV	LTV
($Lend.Std$)	Maturity	Maturity
	LTP	LSTI
		LTI
Mortgage/borrower/collateral	Second-hand	Employment status
characteristics (Z)	Subsidised-housing	Remortgage
		Non-RREcollateral
		Second-home
		Variable-rate
Fixed effects	Region	Region
	Year of origination	Year of origination
		Bank

In particular, we estimate the effect of LTV and LTP, which are our collateral-based indicators. All previous studies assessing the relationship between lending standards and defaults include LTV as the standard indicator of loan quality related to leverage, and find a positive effect on default rates (May and Tudela, 2005; Lazarov and Hinterschweiger, 2018). Nonetheless, as we suspect from the inspection made in Section 4, LTP may capture better this relationship. Previous studies do not include LTP either because they assume that LTV is not biased or because of lack of information on transactions prices.[16] *Maturity* represents the time

16 Raya (2018) is the only previous study that includes this variable as a determinant of problematic mortgages. The author finds a positive relationship with the rate of foreclosures in Spain. However, this study does not include LTV or other lending standards indicators.

to the expected redemption of loans (in years). Qi and Yang (2009) find it to be a relevant determinant of the loss given default. Nonetheless, this variable has been little studied in the literature. Finally, LSTI is the indicator relating the loan service to the borrower's income.[17] This variable has been included before in studies investigating determinants of defaults, finding a positive relationship (Böheim and Taylor, 2000; Kelly and O'Toole, 2018). Overall, we expect poorer lending standards to increase the probability that a mortgage loan becomes problematic.

Additionally, we estimate a vector of binary variables ($\boldsymbol{Z_i}$) that captures the purpose of the loan, as well as additional characteristics of the borrower, the mortgage contract and the collateral. In particular, we consider whether the loans' collateral is a second-hand dwelling *(second-hand)* or a government subsidised housing *(subsidised-housing)*. We incorporate these two variables as proxies of income-related characteristics when income information is not directly available (CdR dataset). We expect a positive relationship of these variables with risk as long as they proxy for loans taken out by low-income borrowers. Income-related characteristics have been found to be important determinants of defaults in previous studies (Lambrecht *et al.*, 2003; Fuster and Willen, 2017).

When using data from the ED, we are able to include directly information of the borrowers as well as additional loan characteristics such as: i) the employment status of the borrower (wage-earner, civil servant, self-employed, unemployed and other occupations); ii) whether the mortgage has been refinanced *(remortgage);* iii) whether households have pledged non-residential/commercial collateral to acquire the dwelling *(non-RREcollateral);* iv) whether the purpose of the loan is to buy a second property *(second-house)* instead of the main home; and v) the interest rate regime of the loan *(variable-rate mortgage).* The relationship between these variables and default has been analyzed before in some few studies. Lazarov and Hinterschweiger (2018) find that the type of employment is releted to mortgage distress given that some occupations are more exposed to income shocks (e.g. self-employed versus civil servants). Haughwout *et al.* (2016) find that re-mortgages have a very high default probability. Campbell (2013) show divergent results in the association between risk and the interest rate regime of the mortgages.

Finally, we include fixed effects for the region (province) where the mortgage was originated and the year in which the loan was granted. This allows us to control for specific characteristics of loans and borrowers across regions as well as for time effects including macro-financial conditions common to all loans in certain periods of time. With ED data, we are also able to include bank fixed effects in order to control for banks' characteristics and lending policies.[18]

17 In Annex 2, we also estimate the main equation by using LTI instead of LSTI. Results are found to be robust to the use of this measure. Due to high collinearity, however, we do not model simultaneously LTI and LSTI.

18 In addition, we expect signs in coefficients linked to year effects to be positive immediately before the crisis, when conditions in real estate credit were buoyant. Signs of coefficients that summarize region effects are expected to be correlated with the severity of the crisis in each area. Bank effects would reflect the riskiness of banks' lending policies not captured by lending standards. We do not show these estimates in our paper but they are available upon request.

6 Results

In this section, we first analyze the relationship between lending standards and defaults after identifying the statistical significance of these effects and previous findings in the literature. Then, in section 6.1, we explore potential non-linearities and the interaction between lending standards while focusing on the economic relevance of the results. Finally, we address how the position in the financial cycle affects the identified relationships (section 6.2).

We estimate ten different models based on the previous general specification by imposing constraints on the coefficients.[19] In particular, in Table 3 we present the results of the estimations using CdR data and in Table 4 those of the models using the ED repository. We first estimate a baseline model including only the two lending standards metrics available in both datasets, LTV and maturity, as well as common controls and the same sample period. Model 1A (Table 3) and Model 1B (Table 4) collect the results. We identify significant and positive effects of both lending standards variables on the probability of default, evidencing their importance as determinants of default risk, and confirming that these effects are identified in spite of the different properties of the two databases.

More specifically, LTV has a significant effect under all the specifications, confirming that higher leveraged loans represent a higher risk at origination. This finding is aligned with previous studies (see Wong *et al.*, 2011, for a cross-country study). Also, we find a significant and positive statistical relationship between loan maturity and the probability of failure across all the models as well. This may reflect the higher indebtedness of these borrowers during the first years of the mortgage, when they are more sensitive to shocks (Haughwout *et al.*, 2008), and the possibility that loans with longer terms are assigned to borrowers with poorer repayment capacity (IMF, 2013; Leal and Lima, 2018).

To address concerns that the LTV may be subject to biases, we include LTP in the model. As previously described, by doing this we lose observations as we need to match different datasets within the CdR. While in section 7.2 we check that this matching process is not introducing biases, we further confirm this by comparing specifications before (Model 2A) and after the merge (Model 2B). The identified effects are consistent and the magnitude of the estimated log-odds coefficients are very similar, with some differences regarding the point estimates of the parameters associated with maturity and second-hand variables.

In Model 3 we incorporate LTP as an additional variable. We find that the impact of LTP on default risk is positive and significant. Furthermore, the log-odds coefficient is higher than the estimated for LTV, while the estimated coefficient of LTV is lower than in the former models. This suggests that marginal effects of LTP are larger than LTV (a more detailed analysis is presented in Section 6.1), and that the differences between appraisal values and purchasing prices may be masking vulnerabilities in the mortgage market.

We also find that characteristics that may be associated with borrowers' income, such as loans in which the collateral is a second-hand dwelling or a subsidised property, have a positive and significant impact on default risk (models 2 to 5). These variables are intended to proxy for the incidence of medium to low-income borrowers on the default probability, since the CdR dataset does not include information on borrowers' income.

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19 Our results are robust to the estimation of alternative specifications (probit and linear probability models) as well as to alternative definitions of problematic loans. Results are presented in Annexes 3 and 4.

Table 3. Estimation Results. Lending standards indicators and problematic loans.
CdR database

	Model 1A	Model 2A	Model 2B	Model 3	Model 4	Model 5
LTV	0.0148***	0.0149***	0.0149***	0.0083***	0.0196***	0.0179***
Maturity	0.0020***	0.0032***	0.0251***	0.0176***	0.0599***	0.0473***
LTP				0.0111***	0.0419***	0.0369***
LTV^2					-0.0001***	-0.0001***
Maturity^2					-0.0008***	-0.0009***
LTP^2					-0.0001***	-0.0001***
LTV x LTP						0.0001*
LTP x Maturity						0.0002***
Second-hand		0.3756***	0.2993***	0.2641***	0.2582***	0.2563***
Subsidised-housing		0.1886***	0.1896***	0.1693***	0.1792***	0.1781***
Region effects	Y	Y	Y	Y	Y	Y
Origination year effects	Y	Y	Y	Y	Y	Y
McFadden R^2	0.048	0.051	0.079	0.088	0.092	0.093
AUROC	0.707	0.713	0.767	0.781	0.783	0.790
BIC	548,409	544,469	109,849	109,671	109,274	109,268
Log-pseudolikelih.	-273,677	-271,681	-54,855	-54,337	-54,118	-54,093
Observations	5,510,673	5,510,673	1,255,649	1,255,649	1,255,649	1,255,649

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and 1%, respectively. The table shows the log-odds of a logit model in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, the LTV is the loan-to-value ratio, the Maturity is the duration of the mortgage at origination, LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries. Second-hand is a dummy equal to one if the mortgage collateral is a second-hand dwelling. Subsidised-housing is a dummy equal to one for government subsidised housing. The specifications add binary variables to control for the region and year in which loans were originated. Model 1A includes the only two variables (LTV and maturity) that both databases (CdR and ED) have in common, as well as common controls and the same sample period. All errors are robust clustered at the loan level. Besides the R-squared and the value of the log likelihood statistic, we also present the AUROC and BIC as predictive performance and goodness of fit indicators. The AUROC (Area under the Receiver Operating Characteristics Curve) assesses the relationship between the false positive and the true positive rates for every probability threshold, providing a measure of the probability that the model predictions are correct. A value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment. The BIC (Bayesian Information Criterion) is an estimate of a function of the posterior probability of a model being true while penalizing for model complexity, so that a lower BIC means that a model is more likely to be the true model.

Evidence is more compelling when data from the ED is used, as we directly observe borrowers' income at origination (Table 4). In particular, in models 6 to 8 we identify that LSTI has a significant and positive impact on default risk, suggesting that the repayment capacity of the borrower is a key variable determining default risk (even when measured at origination). We obtain the same result when LTI is included instead (see Annex 2). These findings are consistent with previous empirical literature identifying debt service to be a key determinant of mortgages defaults (Lambrecht *et al.*, 2003; Haughwout 2008; Fuster and Willen, 2017).

Moreover, models using the ED repository also allow us to include other borrowers' characteristics related to cash flow such as the employment status. We find that the job status is relevant explaining mortgages default risk. In particular, being unemployed or having less stable jobs (e.g. self-employed) increases risk, while more stable jobs (e.g. civil servants) lowers the probability of default.[20]

20 This finding is somehow intuitive but opposite to that in Raya (2018), who did not identify differences between temporary and permanent jobs.

In models 6 to 8, we also control for other contract characteristics such as the purpose of the loan and the type of collateral. In general, we find that remortgages have a higher default risk, which is consistent with previous results in the literature. Tracy and Wright (2016) find that borrowers do not benefit from remortgages or refinancing because they are already constrained. In fact, Haughwout *et al.* (2016) find that the average default rate of remortgages is around 56% in the US (see Lazarov and Hinterschweiger, 2018, for similar results in the UK). By type

Table 4. Estimation Results. Lending standards indicators and problematic loans. ED database

	Model 1B	Model 6	Model 7	Model 8
LSTI		0.0032***	0.0034***	0.0024***
LTV	0.0199***	0.0156***	0.0188***	0.0161***
Maturity	0.0203***	0.0271***	0.0730***	0.0266***
LSTI^2			-0.0000	-0.0000
LTV^2			-0.0001***	-0.0001***
Maturity^2			-0.0008***	-0.0011***
LSTI*Maturity				-0.0000
LSTI*LTV				0.0001***
LTV*Maturity				0.0003***
status: civil servant		-0.861***	-0.861***	-0.861***
status: unemployed		0.653***	0.658***	0.664***
status: self-employed		0.459***	0.461***	0.466***
Remortgage		0.848***	0.863***	0.864***
Non-RREcollateral		0.482***	0.522***	0.539***
Second_home		0.244***	0.257***	0.258***
Variable-rate mortgage		-0.629***	-0.624***	-0.633***
Region effects	Y	Y	Y	Y
Origination year effects	Y	Y	Y	Y
Bank effects	N	Y	Y	Y
McFadden R2	0.080	0.160	0.160	0.160
AUROC	0.736	0.824	0.824	0.825
BIC	416,379	390,370	390,259	390,148
Log-pseudolikelihood	-207,722	-194,225	-194,148	-194,071
Observations	1,407,922	1,674,398	1,674,398	1,674,398

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and 1%, respectively. The table shows the log odds of a logit model in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, the LSTI is the loan service-to-income ratio, LTV is the loan-to-value ratio, and the Maturity is the duration of the mortgage at origination. The baseline case for the categorical variables that refer to the employment status of borrowers is a wage earner. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). The specifications further add categorical variables to control for the region and year in which loans were originated, as well as bank effects (except for Model 1B). Model 1B includes the only two variables (LTV and maturity) that both databases (CdR and ED) have in common, as well as common controls and the same sample period. All errors are robust clustered at the loan level. Besides the R-squared and the value of the log likelihood statistic, we also present the AUROC and BIC as predictive performance and goodness of fit indicators. The AUROC (Area under the Receiver Operating Characteristics Curve) assesses the relationship between the false positive and the true positive rates for every probability threshold, providing a measure of the probability that the model predictions are correct. A value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment. The BIC (Bayesian Information Criterion) is an estimate of a function of the posterior probability of a model being true while penalizing for model complexity, so that a lower BIC means that a model is more likely to be the true model.

of collateral, mortgages with a commercial property as collateral increase the probability of default. This might reflect that these loans are dedicated to business activities, typically riskier than residential mortgages. Loans on second-home properties are more prone to default, too. Finally, mortgages with a variable interest rate regime seem less risky.[21] Probably, the drop in main reference rates since the crisis has benefited variable-rate borrowers, reducing defaults in this segment (we cover this issue more in detail in section 6.2).

6.1 Non-linearities

In order to study more in depth the relationship between lending standards and risk, we explore potential non-linearities. Non-linear effects of lending standards at loan origination on default have been little explored before. Some few studies have found evidence of non-linear effects of LTV and DSTI (Haughwout et al, 2008; Kelly and O'Toole, 2018). We perform this analysis by including quadratic terms of lending standards and interactions.[22] In general, we find that most of the quadratic and interaction terms are statistically relevant (see tables 3 and 4). Moreover, models including these effects provide better performance results than strictly linear models. The negative coefficients of the quadratic terms in the specifications would indicate that the effect of looser lending standards on risk is positive but marginally decreasing. The estimated coefficients of interactions terms are all positive and significant, as expected, except for the one relating LSTI with maturity.

To shed more light on the implications of the previous findings, which are relevant from an economic perspective and for policy issues, we evaluate the logistic function at representative values of these indicators, using the models with the best indicators of predictive performance and goodness of fit (models 5 and 8, using CdR and ED data, respectively). We also compare the results with the linear specifications.[23]

6.1.1 QUADRATIC EFFECTS

In Figure 3 we observe that modeling non-linear effects has important implications on the predicted probabilities and the estimated marginal effects. Figure 3.A shows that the more flexible specification identifies important decreasing effects for high values of LTV, which are not observed in the linear model. In particular, the marginal effect of increasing LTV by 10pp is only significant for levels of LTV lower than 90%. From a policy perspective, this would imply that only caps below this value would have a relevant effect on reducing the default probability. Some few empirical studies have previously identified non-linear relationships of LTV (May and Tudela, 2005; Qi and Yang, 2009; Kelly and O'Toole, 2018).

Interestingly, marginal effects are much higher for LTP (Figure 3.B). In fact, the marginal effect of a 10pp change is much greater for LTP than for LTV. The increase in the probability of default seems to be particularly high within the range 80%-120%. Certainly, the probability doubles between these two values. This is very relevant given that almost half of the mortgages granted before the crisis had a LTP within this range, and almost one-third presented a LTP greater than 120%. The magnitude of this change in default probability is similar to that identified by Haughwout *et al.* (2008) and Kelly and O'Toole (2018) when

21 In this regard, Campbell (2013) finds that the riskiness of mortgages depends on the duration of the period for which the interest rate remains fixed.

22 We also explore other types of non-linearities through discrete transformations of lending standards (section 7.1 presents one of these exercises). In general, including quadratic terms and interactions presents better fit and predictive performance.

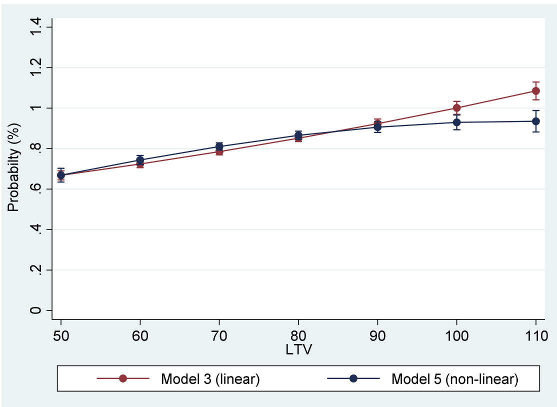
23 We consider that this exercise is more informative than computing the average marginal effects given the importance of the non-linearities and the interactions that are identified when estimating the models.

modeling non-linearities of LTV in the US and the UK, respectively. These findings would confirm that LTP discriminates more properly ex-ante risk associated to leverage than LTV, given that the latter measure is subject to biases. We can also observe that the specification that does not capture non-linear effects may underestimate the marginal effects for LTP above 90%, and overestimate them for lower LTP values.

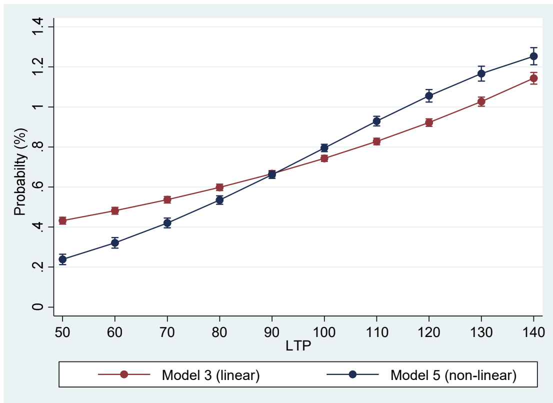
Regarding maturity (Figure 3.C), we also observe that increasing the term of the loan also has a positive but marginally decreasing impact on the probability of default, which is only captured when the specification explicitly models non-linear effects. In particular, the probability of default of a mortgage with a maturity equal to 30 years is 40% greater than that of loans with a payment term of 15 years; above 30 years, the marginal effect of increasing the mortgage term by 5 years is not significant.

Figure 3. Predicted probability of default at relevant values of lending standards indicators. Individual analysis

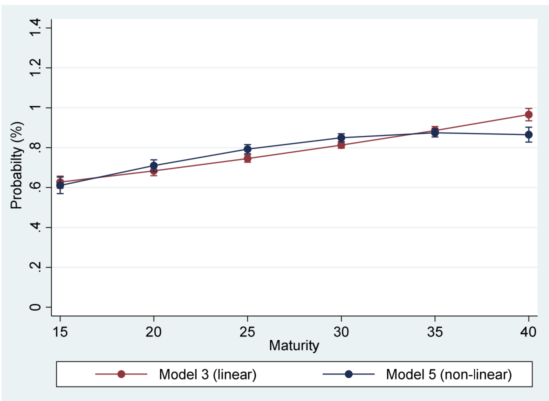
3.A. LTV



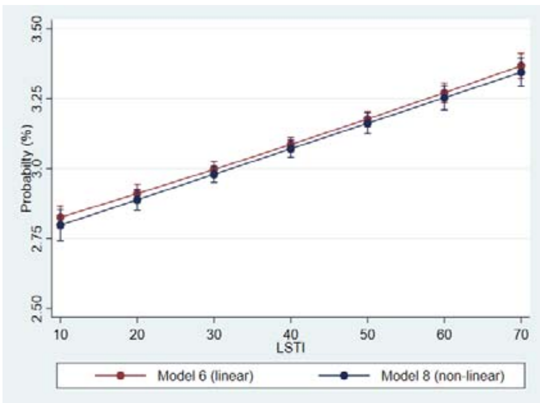
3.B. LTP



3.C. Maturity



3.D. LSTI



Note: Probabilities computed by evaluating the estimated logistic function at relevant values of each lending standards indicator, while holding constant all other characteristics. LTV is the loan-to-value ratio, Maturity is the duration of the mortgage at origination (in years), LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries, and LSTI is the loan-service to income ratio.

Source: Own elaboration using the Colegio de Registradores (CdR) for Figures 3.A to 3.C, and the European DataWarehouse (ED) for Figure 3.D.

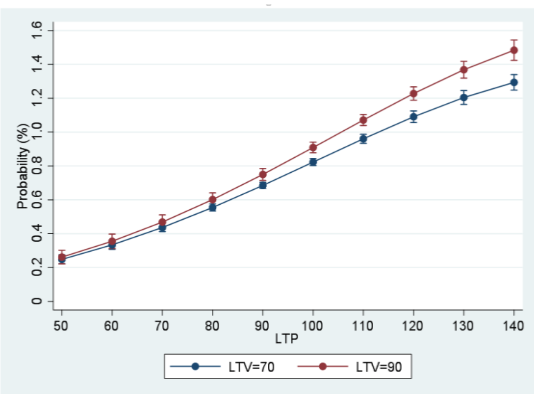
Contrary to the effects identified for the other lending standards, the relationship between LSTI and default probability seems to be relatively linear at the relevant values of the indicator (Figure 3.D). In this regard, findings of previous studies modeling non-linear effects of this variable are diverse but depend on the definition of the measure. Haughwout *et al.* (2008) find that the probability of default increases for a total debt service ratio (DSTI) above 50%. Kelly and O'Toole (2018) show that non-linear effects are only evident for debt service ratios of over 70%, which is not a representative value in the Spanish mortgage market.

6.1.2 INTERACTIONS EFFECTS

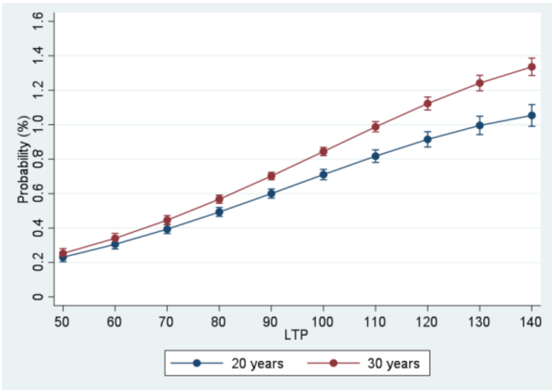
The effects of the interactions can also be observed in terms of predicted probabilities and marginal effects (Figure 4). The interaction of LTP with LTV (Figure 4.A) is positive and statistically significant, although weak, which may reflect that both variables capture the same risk dimension. Indeed, differences in default probabilities between mortgages with low and high

Figure 4. Predicted probability of default at relevant values of lending standards indicators. Joint analysis

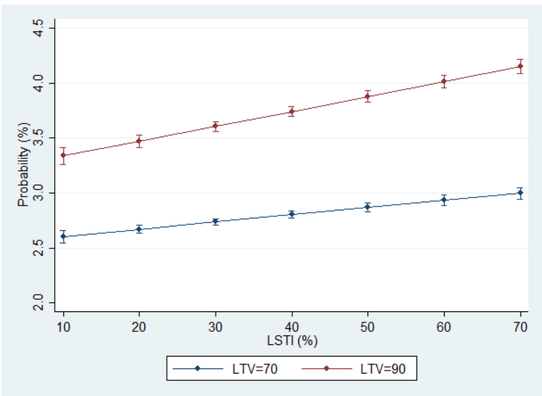
4.A. LTP and LTV



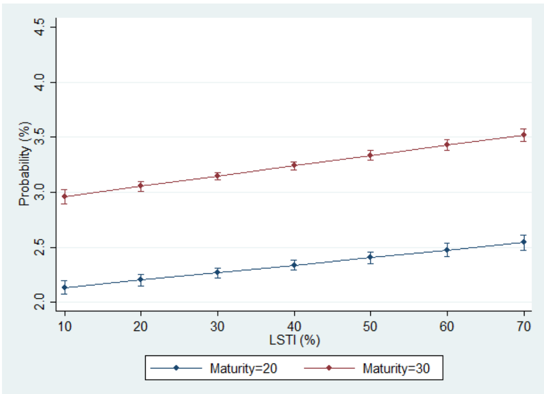
4.B. LTP and maturity



4.C. LSTI and LTV



4.D. LSTI and maturity



Note: Probabilities computed by evaluating the estimated logistic function at relevant values of each lending standards indicator while holding constant all other characteristics. LTV is the loan-to-value ratio, Maturity is the duration of the mortgage at origination (in years), LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries, and LSTI is the loan-service to income ratio. We have also performed the analysis for the models including LTI instead of LSTI, and conclusions are similar.

Source: Own elaboration using the Colegio de Registradores (CdR) for Figures 4.A to 4.C, and the European DataWarehouse (ED) for Figure 4.D.

LTV are only significant for LTP values above 90%. Additionally, loans featuring high LTP coupled with elevated maturities are riskier as well (Figure 4.B). Interactions effects are here somewhat stronger than in the previous case, although again only material for high LTP values.

On the other hand, the interaction between LSTI and LTV is positive and statistically significant in explaining default risk (Figure 4.C). This would suggest that mortgages more vulnerable to cash flows and net equity shocks *(double-trigger)* represent a higher risk (Campbell and Cocco, 2015; Fuster and Willen, 2017). In terms of default probabilities, we find that the risk level is higher for loans with high LTV and that the marginal effect of LSTI is slightly higher for these mortgages. Besides, longer mortgage terms increase the risk level at every LSTI value but there are no evident differences in terms of marginal effects (Figure 4.D). This is aligned with results in Table 4, where the interaction between LSTI and maturity is not statistically relevant.

6.2 Lending standards and risk over the cycle

6.2.1 HAVE MORTGAGES SIMPLY FAILED AS A RESULT OF THE CRISIS?

The crisis that hit the Spanish economy was sizable: according to the Spanish Statistical Office, from peak to trough the cumulative drop in GDP reached 9.6%, while house prices decreased by 37.2% in nominal terms. Against this backdrop, our concern is that defaults in mortgages do not react to poor lending standards at origination, as we have identified, but simply to the crisis shock.

To address this issue, we introduce time effects in our specification. In particular, we take advantage of some features of the ED database. Contrary to the CdR, in the ED repository loans are observed every year (or at a higher frequency) until they mature, they are redeemed or they go into default. After pooling the data, we propose a panel specification based on the same general specification used before, where our set of lending standards metrics enter as time-invariant covariates, since we are only interested in their value at origination.

We present the results for this specification in Table 5. To check that the panel structure does not alter the relationships that we have already identified, we first run the model without considering time effects (Model 9). Then, and given the purpose of this robustness exercise, we add time effects in the estimation, which allows us to control for overall cyclical conditions (Model 10). In both regressions we find similar relationships as well as log-odds coefficients of similar magnitude than those documented previously. This suggests that once income and price shocks act as triggers, lending standards at origination hold as key measures discriminating risk.[24] This finding is consistent with previous studies assessing the effect of lending standards at origination and the cycle. Haughwout *et al.* (2008) find that although the adverse conditions in the first stage of the crisis in the US explained a large part of mortgages defaults, lending standards remain as significant determinants of the default probability. Similarly, Kelly and O'Toole (2018) find that LTV and debt service ratio at origination are more explicative of defaults than the current values affected by the cycle in the UK. This, of course, does not necessarily imply that the effect of these variables remains unchanged over the cycle, as we will show in the following section.

24 These results do not imply that the probability of default is the same at any period. In fact, loans are more likely to default in bad times than during normal/good times. This is corroborated by the estimates of time effects, which are markedly negative immediately before the crisis and turn positive later on. In particular, we find that odds of default reach a maximum in 2013 (final stage of the crisis), which is aligned with Banco de España supervisory information.

Finally, in Model 10 we also study whether the default rate of variable-rate loans is lower than that of fixed-rate loans after controlling for changes in the EURIBOR. The impact of EURIBOR changes for variable-rate loans *(Variable-rate mortgage x dEURIBOR)* is, as expected, statistically significant and positive. That is, an increase in the EURIBOR leads to more failures in variable-rate than in fixed-rate loans. Still, variable-rate mortgages would stand as safer loans as evidenced by the negative sign in the variable-rate dummy, of course, in the absence of large increases in the EURIBOR. In this regard, it is important to remark that fixed-rate mortgages have not been very common in Spain until recently (in our sample, they represent 4% of total loans). Therefore, we take this outcome with caution.

Table 5. Estimation results. Lending standards and problematic loans. ED database, panel data

	Model 9	Model 10
LSTI	0.0021***	0.0019***
LTV	0.0154***	0.0157***
Maturity	0.0236***	0.0233***
LSTI^2	0.0000	0.0000
LTV^2	-0.0001***	-0.0001***
Maturity^2	-0.0009***	-0.0009***
LSTI*Maturity	-0.0000	-0.0000
LSTI*LTV	0.0001***	0.0001***
LTV*Maturity	0.0003***	0.0003***
status: civil servant	-0.867***	-0.873***
status: unemployed	0.619***	0.623***
status: self-employed	0.434***	0.439***
Remortgage	0.781***	0.787***
Non-RREcollateral	0.485***	0.489***
Second_home	0.261***	0.269***
Variable-rate mortgage	-0.596***	-0.593***
Variable-rate mortgage x dEURIBOR		0.0018***
Region effects	Y	Y
Origination year effects	Y	Y
Bank effects	Y	Y
Time effects	N	Y
McFadden R2	0.096	0.152
AUROC	0.810	0.865
BIC	646,016	602,913
Log-pseudolikelihood	-321,823	-300,148
Observations	20,039,290	19,335,195

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and1%, respectively. The table shows the log odds of a logit model in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, the LSTI is the loan service-to-income ratio, the LTV is the loan-to-value ratio, and the Maturity is the duration of the mortgage at origination. The baseline case for the categorical variables that refer to the employment status of borrowers is a wage earner. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). dEURIBOR is the annual change in the EURIBOR, in pp. The specifications further add categorical variables to control for the region and year in which loans were originated, as well as bank effects. The second column also incorporates categorical variables to control for time effects (in this case, we miss observations before 2004 since there are not defaults declared before that date –time effects could not be computed–). All errors are robust clustered at the loan level. Besides the R-squared and the value of the log likelihood statistic, we also present the AUROC and BIC as predictive performance and goodness of fit indicators. The AUROC (Area under the Receiver Operating Characteristics Curve) assesses the relationship between the false positive and the true positive rates for every probability threshold, providing a measure of the probability that the model predictions are correct. A value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment. The BIC (Bayesian Information Criterion) is an estimate of a function of the posterior probability of a model being true while penalizing for model complexity, so that a lower BIC means that a model is more likely to be the true model.

6.2.2 ARE THERE DIFFERENTIAL EFFECTS BETWEEN BOOMS AND BUSTS?

The effects of lending standards on default risk could depend on the stage of the cycle. In particular, during booming years there could be a stronger relationship between lending standards and risk than at other times (see Poghosyan, 2019, for recent evidence). Also, marginal effects might change over time. To explore these potential differences, we estimate our preferred specifications (Model 5 and Model 8), and split the sample into two groups. The first one includes the period before the crisis (Model 5a and Model 8a) and the second one starts from the onset of the crisis (Model 5b and Model 8b).

We report the estimation results in Table 6. For models using the CdR database, our results before the crisis (Model 5a) are similar to those obtained for the whole sample. That is, we find that all lending standards related to LTV, LTP and maturity are relevant variables explaining risk, as well as the quadratic terms and interactions. Nonetheless, the log-odds coefficients are greater than those obtained in the baseline specification, which would translate into larger marginal effects of predicted probabilities.

On the other hand, our results using the model with mortgages granted only from the onset of the crisis (Model 5b) show that these relationships are weaker. In this case, we find that LTV is non-significant, and that LTP and maturity (to a lesser extent) hold as relevant risk determinants. The magnitude of the log-odds coefficients is much lower, too. Taken together, this would imply that during non-booming years, lending standards such as LTV and maturity might not be very informative of ex-ante default risk. However, LTP would be a good indicator of risk regardless of the stage of the cycle, although marginal effects would be lower in non-expansionary phases. We, however, take these latter results with care given that we conduct our study close to the period of analysis.

After the onset of the crisis, we also observe lower marginal effects of LTV and maturity in Model 8b (ED data). Nonetheless, the marginal effect of LSTI is larger after the crisis, as implied by greater log-odds coefficients. This may suggest that, in contrast to what we have identified for other lending standards, income-related indicators increase its importance in periods of contraction and recovery, in terms of discriminating risk among borrowers. These results are consistent with recent findings on the differential effects of borrower-based measures during booms and busts (Claessens *et al.*, 2012; Cerutti *et al.*, 2017; Poghosyan, 2019), and may provide important insights for policy implementation.

Table 6. Estimation Results. Lending standards indicators and problematic loans. CdR database

	Model 5a CdR (2004-2008)	Model 5b CdR (2009-2017)	Model 8a ED (1999-2008)	Model 8b ED (2009-2017)
LTV	0.0216***	0.0083	0.0164***	0.0092***
Maturity	0.0745***	0.0259*	0.0285***	0.0105***
LTP	0.0493***	0.0184***		
LSTI			0.0013***	0.0101***
LTV^2	-0.0001***	-0.0001	-0.0001***	0.0001***
Maturity^2	-0.0013***	-0.0000	-0.0014***	-0.0002
LTP^2	-0.0002***	-0.0001*		
LSTI^2			0.0000	0.0000
LTV*LTP	0.0001***	0.0001		
LTP*Maturity	0.0001***	-0.0002		
LTV*Maturity			0.0004***	-0.0002
LSTI*LTV			0.0001***	0.0001***
LSTI*Maturity			0.0004***	-0.0002
Second-hand	0.2742***	0.2056***		
Subsidised-housing	0.1597***	0.3621***		
Civil-servant			-0.844***	-0.744***
Unemployed			0.633***	0.670***
Self-employed			0.459***	0.498***
Remortgage			0.677***	1.593***
Non-RREcollateral			0.558***	0.054
Second-home			0.280***	-0.440
Variable rate			-0.508***	-1.523***
Region effects	Y	Y	Y	Y
Origination year effects	Y	Y	Y	Y
Bank effects	N	N	Y	Y
McFadden R2	0.068	0.098	0.133	0.334
AUROC	0.739	0.810	0.795	0.919
BIC	85,039	23,744	356,160	31,669
Log-pseudolikelihood	-42,070	-11,414	-177,150	-15,223
Observations	675,493	578,398	1,304,842	341,258

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and 1%, respectively. The table shows the log odds of a logit model in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, the LTV is the loan-to-value ratio, the Maturity is the duration of the mortgage at origination, LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries. The LSTI is the loan service-to-income ratio. Second-hand is a dummy equal to one if the mortgage collateral is a second-hand dwelling. Subsidised-housing is a dummy equal to one for government subsidised housing. The baseline case for the categorical variables that refer to the employment status of borrowers is a wage earner. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). The specifications further add categorical variables to control for the region and year in which loans were originated. Models 8a and 8b incorporate bank effects as well. All errors are robust clustered at the loan level. Besides the R-squared and the value of the log likelihood statistic, we also present the AUROC and BIC as predictive performance and goodness of fit indicators. The AUROC (Area under the Receiver Operating Characteristics Curve) assesses the relationship between the false positive and the true positive rates for every probability threshold, providing a measure of the probability that the model predictions are correct. A value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment. The BIC (Bayesian Information Criterion) is an estimate of a function of the posterior probability of a model being true while penalizing for model complexity, so that a lower BIC means that a model is more likely to be the true model.

7 Robustness

7.1 Other non-linearities

Another way to model non-linear effects is to set thresholds from which the relationship of lending standards with default probability may change. With the exception of the study by Kelly and O'Toole (2018), who model cubic splines, previous studies mostly use the same thresholds approach to explore non-linear effects. We perform this analysis departing from the relevant values identified above as representing a higher marginal effect on risk. Then, we replace the continuous lending standards variables by binary indicators. We present the outcome of these estimations in Table 7. We show the results in terms of odds ratios to obtain a clearer interpretation.

Table 7. Estimation results. Thresholds of lending standards. Odds Ratios

	Model 11 **CdR-Thresholds**	**Model 12** **ED-Thresholds**
LTV>80	1.2395***	1.8043***
Mat>25	1.4111***	1.5476***
LTP>100	2.4927***	
LSTI>50		1.2514***
Second-hand	1.3074***	
Subsidised-housing	1.2129***	
Civil servant		0.4174***
Unemployed		1.9595***
Self-employed		1.5914***
Remortgage		2.2182 ***
Non-RREcollateral		1.6089***
Second home		1.2725***
Variable rate		0.5515***
Region effects	Y	Y
Origination year effects	Y	Y
Bank effects	N	Y
McFadden R2	0.087	0.157
AUROC	0.778	0.8220
BIC	109739	391769
Log-pseudolikelihood	-54371	-194924
Observations	1,255,649	1,674,398

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and1%, respectively. The table shows the odds ratios of a logit model in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, LTV>80 if a dummy equal to one for loans with LTV above the 80% threshold. Mat>25, LTP>100, LSTI>50 represent dummies equal to one for loans with maturity, LTP or LSTI above the corresponding thresholds, respectively. Second-hand is a dummy equal to one if the mortgage collateral is a second-hand dwelling. Subsidised-housing is a dummy equal to one for government subsidised housing. The baseline case for the categorical variables that refer to the employment status of borrowers is a wage earner. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). The specifications further add categorical variables to control for the region and year in which loans were originated. Model 12 incorporates bank effects as well. All errors are robust clustered at the loan level. Besides the R-squared and the value of the log likelihood statistic, we also present the AUROC and BIC as predictive performance and goodness of fit indicators. The AUROC (Area under the Receiver Operating Characteristics Curve) assesses the relationship between the false positive and the true positive rates for every probability threshold, providing a measure of the probability that the model predictions are correct. A value of AUROC equal to 1 would indicate perfect predictions, while a value of 0.5 would indicate that the model is not able to improve the predictions coming from a random assignment. The BIC (Bayesian Information Criterion) is an estimate of a function of the posterior probability of a model being true while penalizing for model complexity, so that a lower BIC means that a model is more likely to be the true model.

In general, the indicators of predictive performance and goodness of fit do not improve from those exhibited by the specifications modeling quadratic terms, which remain as our preferred specifications. Non-linear effects are confirmed in this approach. In particular, in the specification using the CdR data (Model 11) we identify 24% higher odds of default for mortgages with LTV greater than 80% than for those below this threshold. This value is much higher when ED data is used for the estimations (Model 12). In this case, the odds of default of mortgages with LTV above the threshold are 80% higher. This probably reflects that we cannot control for LTP in the ED sample. It may also imply that LTV is less biased in the ED repository.

In the case of mortgages with maturity greater than 25 years, the estimated increase in the odds of default is high and similar under both specifications. That is, odds of default are 41% and 54% higher than for mortgages with maturity below 25 years, for models using the CdR and the ED database, respectively. The increase in odds is much greater for mortgages with LTP greater than 100%, where the odds of default are 2.5-fold higher than for loans below this level. This confirms the presence of important non-linear effects, in line with previous findings, and suggests that the LTP ratio is a more informative determinant of risk than the LTV ratio.

Similarly to previous results, we find that *second-hand* and *subsidised-housing* have significant effects on increasing the odds of default (31% and 21%, with respect to new and non-subsidised properties, respectively). We also confirm the importance of LSTI. Our results show that mortgages with LSTI greater than 50% at origination have 25% higher odds of default than those below this threshold. Finally, we confirm other borrower and mortgage characteristics to be relevant, in line with preceding results.

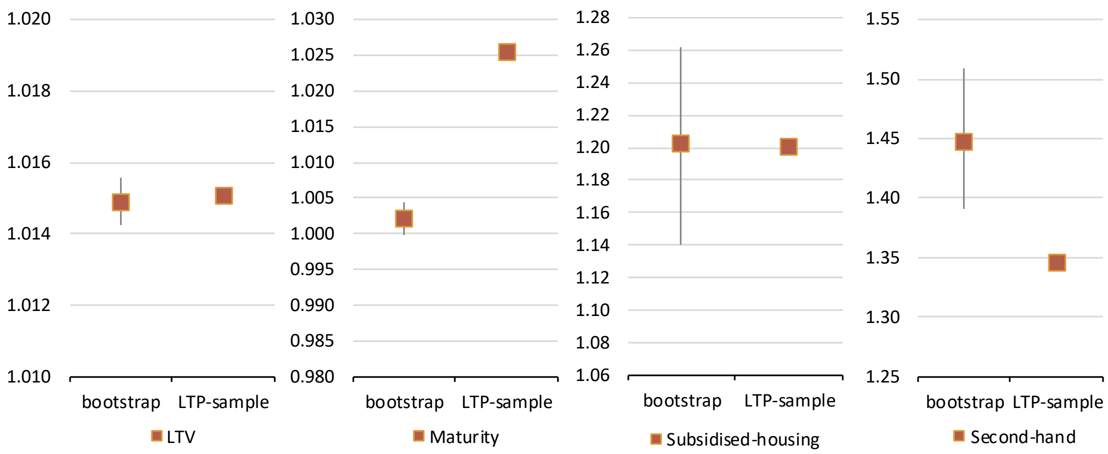
7.2 Addressing potential selection biases: the "LTP-sample"

In order to construct the LTP ratio, we need to merge two different datasets from the CdR. One contains information on the principal amount of loans (numerator of the ratio) and the other one contains the transaction prices (denominator of the ratio). Although there are common variables in these two datasets, it is not possible to reach a one-to-one match. In particular, we find the LTP ratio for 1.3 million loans, which represents 25% of the population of mortgages. Thus, our concern is that matched mortgages present different loan and risk characteristics that may bias the estimated relationships between lending standards and default risk.

To check this issue, we re-estimate Model 2A by using 1,000 random extractions of similar size to our matched "LTP-sample" and bootstrapping the standard errors. We compare the results of these estimations with those obtained from running the same regression for the LTP-sample (Model 2B). We illustrate this comparison in Figure 5 by plotting the point estimates and 95% confidence intervals of each explanatory variable from the bootstrap exercise, along with the point estimate from the "LTP-sample" exercise. We present the outcome in terms of odds ratios for each variable of interest, which facilitates the comparability of the results. In general, the two exercises offer a similar outcome. The estimates of the coefficients of LTV and *subsidised-housing* are not statistically different in both exercises, at the 95% level. The estimates of the coefficients of *Maturity* and *Second-hand* differ, but the difference is of little economic significance, particularly in the former case (odds ratio move from 1.002 to 1.025). Moreover, in both cases (bootstrap and LTP-sample exercises) the evidence is that loans with higher maturities and loans in which the collateral is a second-hand dwelling augment risk.

Overall, our matched "LTP-sample" does not seem to provide significantly different estimates that may introduce biases in our results and affect the identified relationships.

Figure 5. Bootstrap and LTP-sample exercises. Odds ratios



Note: The figure presents the point estimates and the associated confidence intervals for the bootstrap exercise, and the point estimate of the "LTP-sample" exercise (Model 2A). The dots represent the point estimates of the odds ratios, while the whiskers represent the confidence intervals (at 95% level). Confidence intervals for the bootstrap exercise are bias-corrected.

Source: Own elaboration using the Colegio de Registradores (CdR) database.

7.3 Is adverse selection at play in securitisations?

In Spain, banks participate in the ABS market by means of a special purpose vehicle (SPV) or "*fondo de titulización*". Usually, banks sell mortgages and other loans to the SPV, which funds the transaction by issuing ABS. Since investors cannot screen loans in the SPV as banks do, in theory the latter can put *bad* loans in the collateral pool of these vehicles (adverse selection). As a result, securitised mortgages might be of poorer quality than the average mortgage.

There are some reasons to think that the previous mechanism might have not been at play in the Spanish ABS market. First, certain regulatory practices could have prevented banks from redistributing risks. In particular, for securitisations issued after 2004, Spanish banks have been instructed to provide credit enhancement to ABS by absorbing losses in these instruments in the first place (Catarineu and Pérez, 2008). Therefore, banks would have retained a large proportion of risk in securitisations, alleviating incentives to securitise *bad* loans. Second, some authors argue that banks might even be interested in securitising *good* loans. In this respect, Albertazzi *et al.* (2015) find that Italian banks securitised safer (than average) mortgages before the crisis to build a good reputation in the markets. Overall, while the risk-transfer incentive exists, lenders may have not used this mechanism.

To evaluate whether the characteristics of securitised loans are representative of those of the whole portfolio of granted loans, we analyze differences between mortgages reported in the ED and the CdR, which covers the full universe of loans (Annex 5). While there are differences in the distribution of lending standards, it is not clear that these differences imply that loans in the ED repository are riskier. In particular, we do not find that the distribution of LTV of any of the databases is dominant in the first order stochastic sense. The same applies to maturities. Moreover, spreads over risk-free rates (a "catch-up" measure of credit risk) are lower in the latter database, on average. From this, it is not clear that a meaningful downward or upward bias arises in ED data.

8 Conclusions and policy implications

The real estate sector has been a key determinant of previous systemic crises (Jordà *et al.*, 2016). In general, countries that experienced a boom of house prices and credit in the years preceding the last financial crisis also presented a deterioration of lending standards (Kelly *et al.*, 2019). The correlation between the deterioration of lending standards and future systemic crises has been identified in several cross-country studies (Lim *et al.*, 2011; Cerutti *et al.*, 2017).

Most of these studies use the LTV ratio for monitoring purposes and policy implementation. However, LTV may suffer of important biases. The main reason is that banks may circumvent LTV-based regulatory requirements through different means, either by increasing other types of credit, loosening other lending standards not subject to regulatory constraints, or re-allocating their portfolios towards borrowers with a riskier profile (Tzir-Ilan, 2017; Acharya *et al.*, 2019). In Spain, the systematic over-appraising of mortgage collateral distorted LTV values (Duca *et al.*, 2010; Akin et al, 2014; Montalvo and Raya, 2018), thus not reflecting properly the risk of mortgages. In this study, we explore whether or not LTV is able to provide useful signals of ex-ante risk, as well as the relationship between a broad set of lending standards indicators and defaults. For this purpose, we analyze two large datasets at loan-level that include collateral and borrower characteristics of millions of mortgages granted in Spain over a long-time span.

We find that lending standards at loan origination are key measures of ex-ante risk in the mortgage market. Nonetheless, we find that LTV might impair risk identification when this ratio is subject to biases, as those evidenced in Spain during the booming years. We identify LTP and LSTI as the most relevant and robust indicators of ex-ante default risk. We also identify important non-linearities, mainly on the effects of LTV/LTP and maturity on the default probability. Additionally, we find that the interactions of LTP with both LTV and maturity, as well as interactions of LSTI with LTV, are highly relevant for the identification of risk pockets.

Finally, we show that the relationship between lending standards and default risk is dynamic and changes over the cycle. Thus, borrower-based measures may have differential effects during booms and busts, in the same way as interactions between credit and house prices could depend on the stage of the cycle (Claessesn *et al.*, 2012; Cerutti *et al.*, 2017).

Our results confirm the usefulness of borrower-based measures to limit vulnerabilities in the mortgage market, and identify key thresholds for the potential implementation of these tools. This is of increasing importance given the active use of this type of measures in many countries after the last financial crisis (Kelly et al, 2019; Poghosyan, 2019). We also find evidence on the convenience of introducing simultaneously combinations of these measures in order to reduce risk in a more effective way, but also to avoid spillover effects, regulatory arbitrage and other unintended consequences.

Overall, Spain was not different to other countries experiencing a deterioration of lending standards during the last house prices boom. The way Spanish banks dealt with LTV-related constraints evidences some shortcomings of this measure, and suggests the need of considering a richer set of lending standards indicators for risk assessment and subsequent macroprudential policy design and implementation.

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ANNEX 1. Definition of variables

Variable	Source	Definition	Description
Lending standards			
LTV	CdR / ED	Loan-to-value	Numerator: principal amount of the mortgage. Denominator: *appraisal value* of the property.
LTP	CdR	Loan-to-price	Numerator: principal amount of the mortgage. Denominator: *price* of the property (as recorded in land registries).
Maturity	CdR / ED	Maturity (in years)	Initial duration of the loan
LSTI	ED	Loan service-to-income	Share of the gross annual income of the primary borrower dedicated to pay down mortgage debt during the fist year of the loan life. It is calculated on the assumption that all loans follow the French amortization system (equal monthly payments over the life of the loan)
LTI	ED	Loan-to-income	Principal amount of the loan to the annual income of the primary borrower
Dwelling characteristics			
Second-hand	CdR	No new home	Second-hand dwellings are cheaper. They could be targeted by borrowers with below average income
Subsidised-housing	CdR	Owner-occupy housing for low-income borrowers promoted by some public authority	Segment of mortgages in which more vulnerable borrowers have a stronger involvement
Borrower´s characteristics			
Employment status: […]	ED	The base case are wage earners. Other categories include civil servants, unemployed, self-employed, as well as loans to students and pensioners	Less stable job positions or unemployed might be more prone to default
Contract characteristics			
Remortgage	ED	New mortgage financing for a borrower with a previous mortgage	Higher default probabilities if distressed borrowers are more likely to apply for refinancing operations
Non-RREcollateral	ED	Collateral other than a dwelling	Loans for no owner-occupying purposes. Sometimes extended to raise funding for running new businesses
Second_home	ED	No main residence of the borrower	Possibly riskier for borrowers with a mortgage on their main residence/dwelling
Variable-rate mortgage	ED	Interest rate regime is variable, not fixed	Borrowers with variable-rate mortgages benefit from drops in interest rates, and face a higher debt service when interest rates rise
Macro variable			
dEURIBOR	*Thomson Reuters Eikon*	Annual change in the EURIBOR (pp)	The EURIBOR is the benchmark interest rate for the vast majority of Spanish variable-rate mortgages

Source: own elaboration.

ANNEX 2. LTI Ratio

	Model A1	Model A2	Model A3
LTI	0.0158***	0.0028	0.0069***
LTV	0.0160***	0.0199***	0.0166***
Maturity	0.0271***	0.0787***	0.0283***
LTI^2		0.0007***	0.0005**
LTV^2		-0.0000***	-0.0001***
Maturity^2		-0.0009***	-0.0011***
LTI*Maturity			-0.0009***
LTI*LTV			0.0005***
LTV*Maturity			0.0003***
status: civil servant	-0.864***	-0.865***	-0.865***
status: unemployed	0.627***	0.632***	0.637***
status: self-employed	0.440***	0.439***	0.443***
Remortgage	0.817***	0.833***	0.833***
Non-RREcollateral	0.468***	0.510***	0.523***
Second_home	0.249***	0.258***	0.261***
Variable-rate mortgage	-1.896***	-1.887***	-1.890***
Region effects	Y	Y	Y
Origination year effects	Y	Y	Y
Bank effects	Y	Y	Y
Observations	1,683,031	1,683,031	1,683,031

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and 1%, respectively. The table shows the log odds of a logit model in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, the LTI is the loan-to-income ratio, the LTV is the loan-to-value ratio, and the Maturity is the duration of the mortgage at origination. The base case for the categorical variables that refer to the employment status of borrowers are wage earners. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. Second-home is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). The specifications further add categorical variables to control for the region and year in which loans were originated, as well as bank effects. All errors are robust clustered at the loan level.

ANNEX 3. Robustness to other specifications: probit and linear probability model

	Model A4 CdR-Probit	Model A5 CdR-LPM	Model A6 ED-Probit	Model A7 ED-LPM
LTV	0.0056***	0.0001***	0.0069***	0.0005***
Maturity	0.0149***	0.0001***	0.0117***	0.0007***
LTP	0.0109***	0.0001***		
LSTI			0.0010***	0.0001***
LTV^2	-0.0001***	-0.0000***	-0.0000***	0.0000***
$Maturity^2$	-0.0003***	-0.0000***	-0.0005***	-0.0001***
LTP^2	-0.0001***	-0.0000***		
$LSTI^2$			-0.0000	0.0000*
LTV x LTP	0.0000**	0.0000***		
LTP x Maturity	0.0001***	0.0000***		
LTV*Maturity			0.0002***	0.0000***
LSTI x LTV			0.0001***	0.0000***
LSTI x Maturity			0.0000	0.0000***
Second-hand	0.099***	0.002***		
Subsidised-housing	0.072***	0.002***		
Civil-servant			-0.360***	-0.0101***
Unemployed			0.315***	0.0216***
Self-employed			0.234***	0.0137***
Remortgage			0.420***	0.0356***
Non-RREcollateral			0.268***	0.0235***
Second_home			0.136***	0.0060***
Variable rate			-0.284***	-0.0109***
Region effects	Y	Y	Y	Y
Origination year effects	Y	Y	Y	Y
Bank effects	N	N	Y	Y
Observations	1,255,649	1,255,649	1,674,961	1,674,961

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and 1%, respectively. The table shows the estimates of probit and linear probability models (LPM), in which we assess the probability of a mortgage to go into default given certain loan characteristics. Within the explicative variables, the LTV is the loan-to-value ratio, the Maturity is the duration of the mortgage at origination, LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries. The LSTI is the loan service-to-income ratio. Second-hand is a dummy equal to one if the mortgage collateral is a second-hand dwelling. Subsidised-housing is a dummy equal to one for government subsidised housing. The baseline case for the categorical variables that refer to the employment status of borrowers is a wage earner. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). The specifications further add categorical variables to control for the region and year in which loans were originated, as well as bank effects in the case of models A6 and A7. All errors are robust clustered at the loan level.

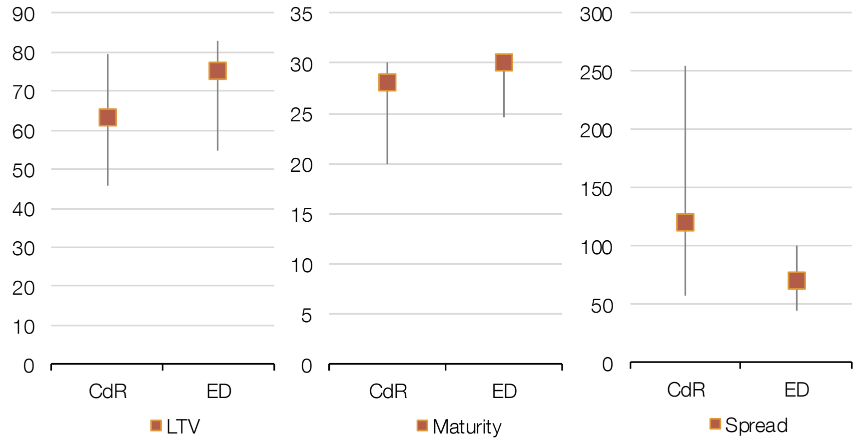
ANNEX 4. Other definitions of default: foreclosures and arrears

	Model A8 CdR-Foreclosures	Model A9 ED-Defaults & arrears	Model A10 ED-Only arrears
LTV	0.0033***	0.0164***	0.0092***
Maturity	0.0016**	0.0285***	0.0105***
LTP	0.0047***		
LSTI		0.0014***	0.0101***
LTV^2	-0.0001***	-0.0001***	0.0001***
$Maturity^2$	0.0002***	-0.0014***	-0.0003
LTP^2	-0.0001***		
$LSTI^2$		0.0000	-0.0000
LTV x LTP	0.0001*		
LTP x Maturity	0.0001		
LTV x Maturity		0.0004***	-0.0002
LSTI x LTV		0.0001***	0.0001***
LSTI x Maturity		-0.0001*	0.0001
Second-hand	1.9290***		
Subsidised-housing	0.2125***		
Civil-servant		-0.844***	-0.744***
Unemployed		0.633***	0.670***
Self-employed		0.459***	0.498***
Remortgage		0.677***	1.593***
Non-RREcollateral		0.558***	0.054
Second_home		0.280***	-0.440
Variable rate		-0.508***	-1.523***
Region effects	Y	Y	Y
Origination year effects	Y	Y	Y
Bank effects	N	Y	Y
Observations	1,094,463	1,304,842	341,258

Note: *,**,*** represent that the coefficient is statistically significant at 10%, 5% and 1%, respectively. The table shows the log odds of a logit model in which we assess the probability of a mortgage to become problematic given certain loan characteristics. A loan is problematic if it has been repossessed (Model A8) or if it has gone into default or is in arrears (Model A9) or if it is only in arrears, but not defaulted (model A10). Within the explicative variables, the LTV is the loan-to-value ratio, the maturity is the duration of the mortgage at origination, LTP is the loan-to-price ratio, where price is the dwelling price as recorded in land registries. The LSTI is the loan service-to-income ratio. Second-hand is a dummy equal to one if the mortgage collateral is a second-hand dwelling. Subsidised-housing is a dummy equal to one for government subsidised housing. The baseline case for the categorical variables that refer to the employment status of borrowers is a wage earner. Within this subset, there is an additional category ("other"), which groups loans to students, pensioners, and other items. For ease of presentation, this variable is omitted in the table. Remortgage is a dummy that indicates whether the mortgage has been refinanced. Non-RREcollateral is a dummy equal to one when the collateral of mortgages is not a dwelling. *Second_home* is a dummy equal to one for this type of properties. Variable-rate mortgages correspond to mortgages with this interest rate regime (no fixed-rate contracts). The specifications further add categorical variables to control for the region and year in which loans were originated, as well as bank effects for models A9 and A10. All errors are robust clustered at the loan level.

ANNEX 5. Differences between CdR and ED databases

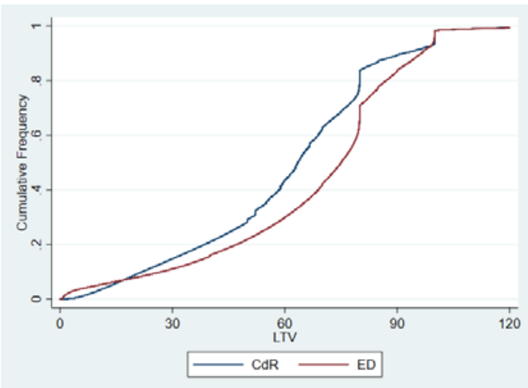
Figure A1. Loans characteristics in the CdR and the ED repository



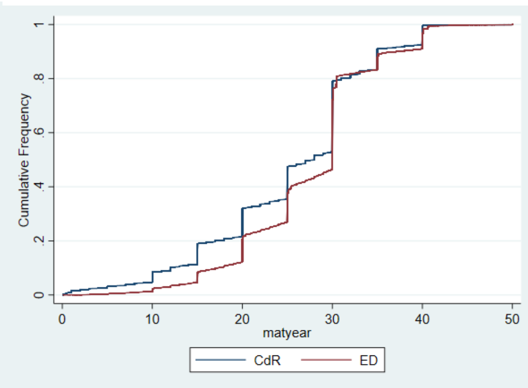
Note: The figure presents the median (dots) and the interquartile range (whiskers) of the corresponding indicator. LTV is a ratio (%). Maturity is measured in years. Spread is the spread of mortgages over the risk-free rate, measured in basis points. The benchmark curve (risk-free rates) for calculating the spread is that of the euro interest rate swap. The benchmark maturity sector is one year for floating rate mortgages. For fixed-rate loans, it coincides with the maturity of these contracts. CdR stands for the statistics of indicators in this database, while ED refers to the same statistics for securitised credit.

Figure A2. Cumulative distribution of lending standards (CdR and ED)

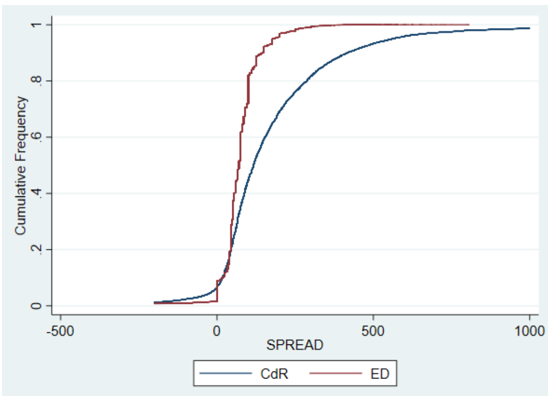
Panel A. LTV ratio (%)



Panel B. Maturity (years)



Panel C. Spread (basis points)



Note: In Panel A the figure presents the cumulative distribution of the LTV ratio of mortgages. In Panel B the figure presents the cumulative distribution of the maturity of mortgages, measured in years. In Panel C the figure presents the cumulative distribution of the spread of mortgages over the risk-free rate, measured in basis points. The benchmark curve (risk-free rates) is that of the euro interest rate swap. The benchmark maturity sector is one year for floating rate mortgages. For fixed-rate loans, it coincides with the maturity of these contracts.

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