Debt-to-income and Loan-to-value ratios as credit risk indicators: Evidence from France and implications for macroprudential policy.

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Preliminary – Do not quote

January 2023

Abstract

The association between lending standards caps, typically based on loan-to-value (LTV) and/or debt-service-to-income (DSTI) levels and credit risk contributes to the effectiveness of macroprudential policies related to housing finance. Using a database of more than two million French home ownership loans issued from 2000 to 2016, we first show that borrowers' default risk is not so much identified by a high DSTI level (≥35%), the main instrument of the recently introduced French policy, as by a high LTV level (e.g. ≥100%). Our analysis of the interaction of the two ratios shows that the likelihood to be a high-LTV borrower may be associated to a decrease in the likelihood to be a high-DSTI borrower. That weakens the relationship between DSTI and borrowers' risk relative to LTV. This reflects the adjustments made by borrowers and lenders in order to manage DSTI ratios, limiting their growth while LTV, and risk, increase. Then, we adopt a lender's perspective and show that, across the business cycle, high-LTV loans represented up to 60% of potential lender losses. As these loans represent about 20%-25% of all housing loans, our results cast doubt on the ability of DSTI on its own to curb credit risk in a macroprudential perspective.

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1. Introduction

Since the 2007 Great Financial Crisis (GFC), research has extensively documented how the relaxation of lending standards on housing loans has fueled the growth of house prices and led to the accumulation of credit risk on bank balance sheets (Akerlof *et al*, 2014, Mian and Sufi, 2011, Campbell and Cocco, 2015, Corbae and Quintin, 2015). These findings provide the core justification of macroprudential policies related to housing finance. Indeed, in the aftermath of the GFC, many supervisors have considered caps on lending standards as relevant tools for the design of macroprudential policies (CGFS, 2012, 2016). Two main effects were expected. First, such caps would restrain households' demand of credit in order to relieve the pressure on the growth of house prices. In that perspective, a vast empirical research has shown that such caps moderate credit growth and dampen potential house price bubbles (Duca *et al*., 2012, Crowe *et al*., 2013, Kuttner and Shim, 2016, Cerutti *et al*., 2017, Kelly *et al*., 2018, Armstrong *et al*., 2019). Moreover, caps seem more effective to slow down credit growth than other tools, such as capital buffers (Gambacorta and Murcia, 2019). These first expected effects of caps define a credit demand channel of macroprudential policy. Second, regulatory caps would also prevent the accumulation of risks on the lenders' balance sheets. Indeed, caps may have an impact on the composition of the pool of borrowers and more specifically on its risk. Theoretical models of mortgage default predict that high LTV or DSTI ratios reveal higher borrowers' sensitivity to economic shocks (Laufer, 2018, Campbell and Cocco, 2015, Hatchondo *et al*., 2013). Therefore, caps may limit the overall risk of the population of housing borrowers by controlling the ability of borrow of the potentially weakest borrowers. This second effect identifies a bank resilience channel (He *et al*., 2016), because caps decrease the likelihood of cumulated losses jeopardizing the solvency of lending institutions. The so far scarce research about the effect of caps on credit risk (de Araujo *et al*., 2020, Igan and Kang, 2011) concludes to a risk reduction effect, suggesting the existence of a welfare improving effect of concentrating macroprudential policies on the weakest borrowers, as theoretically analyzed by Punzi and Rabitsch (2018).

Most countries that have implemented macroprudential policies consider Loan-to-Value (LTV) caps as their main instrument. This is the case of most European Union countries[1]. However, recently, some of them have added income-based caps to complement the LTV caps. Most are small European countries. Among the larger European economies, two countries – the UK and France - are the only ones that ground their macroprudential policy on income-based ratios. In 2014, the UK has enforced debt-to-income caps and, in 2019, France has recommended to adopt a debt service to income (DSTI)

[1] For an overview of macroprudential policies in the EU, see ESRB (2021).

limit of 33% coupled with a 20 years maturity limit, these limits being relaxed in 2021 to respectively 35% and 25 years (with a 15% tolerance of loan production beyond the DSTI cap for first homebuyers). These income-based policies seem to be a singular choice in an international perspective that requires further investigation.

This research relates to the bank resilience channel of macroprudential policy. However, the materiality of such a channel depends upon the calibration of caps but also on the propensity of prospective borrowers exceeding the caps to be indeed riskier. Therefore, our objective is to assess the capacity of lending standards to identify effectively riskier loans at origination. To this aim, we first investigate the relationships between the DSTI and LTV ratios and credit risk at the borrower level. Theoretically, large discrepancies in the level of association between each of these two ratios and default risk would suggest that they diverge in their ability to identify risky potential borrowers. Consequently, analyzing the association between specific lending standards (i.e. potential prudential caps) and risk could provide additional guidance in the design of macroprudential policy.

The French home-ownership loans market provides a consistent case to address this issue as the introduction of a formal recommendations is very recent (2019). Therefore, prior origination decisions reflect the lending policies of commercial banks outside any explicit macroprudential framework[2]. However, over the period covered by our data (2000-2020), the share of loans that would have been considered as excessive in terms of lending standards (typically, with a DSTI larger than 33% and/or a LTV larger or equal to 100%) appears to be quite large. Indeed, the weight of these high-DSTI and high-LTV loans represented up to 20-25% of the total production of homeownership loans, fluctuating along the business cycle. Hence, the introduction of macroprudential caps could have material effects on either the lending policies of French banks or the risk level of housing loans.

In this paper, we use a database of French housing loans originated between 2000 and 2020. The database is restricted to loans whose destination is the acquisition of the main residence and it contains about more than two million loans[3] originated by major French commercial banks. As mentioned before, the database also records characteristics of the borrowing households, the acquisition itself, and the loan at the date of origination. It gives also complete information about default dates and recovery rates, allowing the computation of default rates through time but also of effective losses. That allows taking into account heterogeneous loss-given-default rates across loans

[2] Hence, the macroprudential norms introduced in 2019 merely reflected what was considered as sound business practices by the lenders themselves.

[3] More than 3 million after elimination of repurchase loans.

with different LTV and/or DSTI levels. Finally, declining the analyses across subsets of loans issued at different vintages of origination helps evaluating the robustness of our results across the business cycle and/or changes in the stringency of lending standards of French lenders through time.

To address our research question, we implement a three steps research agenda. First, we estimate a default model using two set of variables. The first one characterizes the borrowers (at the household level) such as profession, size and structure of the household, borrowers' age, marital status, households' income, and wealth. The second one characterizes the housing loans such as cost of the acquisition and the loan maturity at the other hand. This allows retrieving expected default probabilities conditional to the borrowers' and loans' characteristics at origination. Then, the computation of average estimated probabilities across LTV and/or DSTI quantiles (percentiles) allows a more precise characterization of the relationships between credit risk and high values of the DSTI and LTV ratios, taking account of possible non-monotonicity and suggesting DSTI/LTV based risk segmentations within the population of borrowers. At this stage, we find, quite unsurprisingly, that default rates on housing loans are positively associated to both higher levels of DSTI and LTV (at origination). However, we find also that the association is stronger for LTV than for DSTI.

In the second step, using the same two previous sets of variables, we model the cross relationships between the LTV and DSTI ratios in order to determine how the two ratios could interact in a way that may weaken the DSTI – risk relationship. This analysis help also identifying the types of financial constraints on the high-DSTI and high-LTV borrowers. The main result we find at this stage is that, for some households, the likelihood to be a high-LTV (≥100%) borrower is associated to a decrease in the likelihood to be a high-DSTI (≥35%) borrower. Hence, some borrowers with DSTI levels lower informal of formal caps nevertheless belong to the riskier segments of the population, which weakens the DSTI – default relationship. This reflects the adjustments made by lenders to the characteristics of loans and acquired housing in order to limit the DSTI level while expanding borrowing to address rising prices. Hence, LTV levels may still increase as DSTI level remain stable, at least for some borrowers. This feature may also reflect competition on credit markets and contribute to the accumulation of risk in a context of increasing house prices.

The third step of our empirical analysis considers the perspective of the lender. The previous analyses considered risk only at the loan level, focusing on individual default probabilities. However, gauging the resilience of lenders requires considering potential aggregated credit losses associated to a wave of correlated defaults. In case of macroeconomic shocks, such as income or house prices shocks, borrowers could default simultaneously, creating a potential concentration of defaults in bank portfolios. Hence, using the framework underlying the Basel credit risk regulations, we expand our analysis in order to compute the aggregate potential losses associated to segments of borrowers based on several lending standards thresholds. Results show that high-LTV loans bear a higher level of systematic risk, what implies a potential concentration of losses at the lender's portfolio level. Hence, in the French case, high-LTV loans (i.e., with no downside payment) represented up to two-thirds of potential losses across the cycle. Hence, our results oblige to consider, as we do in the second step of the paper, the complex interactions between the LTV and DSTI levels, to comply with the macroprudential policy objective that is to limit the origination of high-risk housing loans.

The paper is organized as follows. Section 2 reviews the main literature focusing on the relationships between LTV and DSTI ratios and default risk and the estimated effects of implemented macroprudential policies. Section 3 presents data and documents the link between LTV and DSTI ratios at origination and the level of defaults and losses in different successive vintages of origination. Section 4 presents the default model that allows characterizing the relationships between default risk and lending standards at origination. Section 5 models the interactions between the probabilities of loans to be high-LTV and/or high-DSTI in order to identify the adjustments that may affect the risk - lending standards relationships. In order to highlight the contribution of high-LTV loans to credit risk at the market level, Section 6 develops a credit risk model in order to compute the potential losses of housing loans at the portfolio (lender) level. This allows identifying the potential concentration of credit risk on high-LTV loans and its sensitivity to the credit cycle. Section 7 concludes and discusses the implications of our results for the design of macroprudential policies.

2. Relation to the literature

This research relates to the stream of the literature that considers the resilience channel of macroprudential policies (He et al., 2016)[4]. Here, the issue is to know whether lending limits can prevent housing loans defaults and the accumulation of losses in lenders' portfolios. In brief, a lower LTV is expected to reduce the impact of price shocks on default risk and losses while a lower level of the DTI/DSTI ratio is expected to limit the impact of income shocks on the repayment capacity of

[4] In fact, lending caps could provide an alternative to the Basel 2/3 banking capital regulation. For instance, Claessens et al. (2013) show that lending policies have a stronger impact on bank credit risk than capital buffers policies, Gambacorta and Murcia (2020) that the propagation of capital-based requirements on credit growth is less rapid than the one of macroprudential policies.

borrowers[5]. However, the bank resilience channel is not the one that has attracted the most attention from researchers. In fact, most studies considering lending caps policies focus on the demand channel and they generally show that these policies have been successful in controlling credit cycles and dampening potential house price bubbles[6]. However, the effect of lending limits on credit risk is much less documented (de Araujo et al., 2020). Only few papers consider the impact of the limits policies implemented in various countries on the housing loans risk. However, we can benefit from a vast theoretical and empirical literature dealing with the relationships between lending standards and credit risk to understand the ability of limits to reduce credit risk. Therefore, in this literature review, we consider successively two questions. First, what can we learn from actually used macroprudential policies about the capacity of regulatory limits to control mortgage default? In addition, what can we learn about the relationships between lending standards at origination and the level of mortgage default risk, regardless of any macroprudential policy?

Most papers dealing directly with the impact of limits policies consider mostly the LTV limits, simply because it is the most commonly used instrument (IMF, 2016, ESRB, 2019). Igan and Kang (2011) for South Korea and De Araujo *et al.* (2020) for Brazil show that LTV caps contribute to reduce defaults. Using a panel of Latin-American countries having implemented caps policies, Gambacorta and Murcia (2019) show that the effectiveness of caps on the resilience to risk is verified, but lower than on the control of credit cycle. Morgan *et al.* (2019) on a panel of countries assess their ability to reduce the frequency of non-performing loans. Moreover, de Jong and de Veirman (2019) show that in the Nederland the impact of LTV limits are asymmetric and non-linear as tighter limits constrain a larger fraction of borrowers and they find that an increase in heterogeneity can substantially increase the effects of a change in LTV caps. However, if lending caps are expected to increase the households' resilience to shocks, in particular for the riskier ones, the issue is to verify that the risk reducing capacity of caps may be determined by the propensity of high LTV and/or DSTI borrowers to be riskier, as theoretically analyzed by Punzi and Rabitsch (2018). Thus, the efficiency of macroprudential caps to curb credit risk may be conditioned by their ability to identify risky potential borrowers. Independently from the design and analysis of macroprudential policies, a stream of literature, which has gained in

[5] A similar mechanism applies in case of adjustment of the loans' interest rate (Campbell *et al*., 2020).

[6] Indeed, robust cross-country evidence has established that lending limits could moderate credit growth and dampen potential house price bubbles (Lim *et al*., 2011, Crowe *et al*., 2013, Duca *et al*., 2012, Kuttner and Shim, 2016, Cerutti *et al*., 2017, Kelly *et al*., 2018, Armstrong *et al*., 2019, Gadea and Perez Quiros, 2021, Gambacorta and Murcia, 2020, Richter *et al*., 2019)[6]. Overall, empirical evidence is stronger for the impact of LTV caps on credit growth than on house prices (see Couailler *et al*., 2018, for a review). Thus, Igan and Kang (2011) find that LTV limits reduce the number of house transactions and the house prices in South Korea. Morgan et al. (2019) get the same result in a larger panel of countries. However, Jacome and Mitra (2015) and Darbar and Wu (2015) do not find significant effects on house prices for different countries panel.

importance in the wake of the GFC, aims at identifying the determinants of defaults of housing loans, among which lending standards such as LTV and DSTI/DTI appear to be of first importance.

Concerning the relationships between lending standards and risk, we can learn both from theoretical research and from empirical studies. At the theoretical level, Campbell and Cocco (2015) formalize the fundamental mechanisms that determines mortgage default. They provide a framework for mortgage default that combines financial constraints and negative equity. Default being costly, at low levels of negative equity, financially distressed households would prefer to avoid default, but at high levels of negative equity, they would prefer default. In this context, any decrease of a down payment standard relaxes financial constraints but also increases the likelihood to realize high negative equity levels in the future. Thus, defaults are the result of both income shocks and negative equity. Accordingly, loan characteristics such as LTV and DSTI reflect the adjustments made by borrowers to the income and house price risks they are exposed to, given the lending standards implemented by lenders. Therefore, the main results from the theoretical literature suggest that higher LTV or DSTI ratios may reflect higher financial constraints of borrowers, inducing potential increase of default risk. In that perspective, policies aiming to impose tighter lending standards might help containing default rates and the risk exposure of the lenders (Campbell and Cocco, 2015, Laufer, 2018, Ampudia *et al*., 2021)[7].

However, such features may also lead to non-monotonic relationships between these ratios and credit risk. In fact, LTV and DSTI ratios may not only reflect the financial constraints of borrowing households but also, to a certain extent, their personal finance decisions (Guiso *et al*., 2013, Campbell and Cocco, 2015). Low downside payment may not only reflect the limited amount of savings a household may rely on, but also their decision to mobilize (or not) existing financial assets, especially for wealthier households. Thus, a high LTV ratio may as well reflect high as low financial constraints. Similarly, the interpretation of the role of DSTI ratios may be dependent upon the borrower's income level. Indeed, banks may take into account both the repayment effort as well as the net disposable income, i.e., the household income after (monthly) repayment. High-income borrowers may devote a higher saving capacity to a loan repayment while maintaining appropriate living standards. Thus, a high DSTI ratio may reflect either higher financial constraints on low or intermediate incomes or lower constraints on high-income borrowers. Hence, to some extent, the association between lending standards and financial constraints is an empirical issue.

[7] Notice that policies aiming to promote high legal protection of lenders such as strong recourse (Hatchondo *et al*., 2015) provide a similar result.

The numerous empirical studies that have investigated the relationship between lending standards and delinquency rates have used mainly micro-level data. They verify that LTV and DSTI ratios are of first importance. The importance of LTV at origination as a key variable in credit scoring has been recognized for a long time (Avery *et al*.,1996, Bajari *et al*. ,2008, Galán and Lamas, 2019, Ampudia *et al*., 2021). As Bajari *et al*. (2008) show, this comes from the fact that high LTV ratios at origination reflect primarily liquidity constraints and an overall lower credit quality of borrowers. However, these authors also stress the importance of house price decline in determining default, which underlines the systematic nature of defaults. Other papers focus on the weight of indebtedness ratios (Foote et al., 2009, Johnson and Li, 2010, Quercia *et al.*, 2012, Nier *et al*., 2019, Gaudêncio J. *et al*., 2019) and show the existence of an increasing relationship between the DSTI/DTI ratio and the rate of default. Ceteris paribus, households with higher levels of this ratio are more likely to be hit by income shocks. Empirical evidence also verifies the existence of combined effects of the two ratios (Foote *et al*. 2009, Chan *et al*., 2013, Punzi and Rabitsch, 2018, Gaudêncio *et al*., 2019, Ampudia *et al*., 2021). Chan *et al*. (2013) observe that high levels of LTV and DSTI ratios are correlated to defaults, and a loosening in lending standards leads to a concentration of delinquencies.

An important result that comes from the empirical studies, and especially those that consider the two ratios together, is that the LTV ratio seems to exert a predominant effect on the rate of default. Thus, Foote *et al*. (2009) underline the combined effects of income shocks and the fall in house prices in explaining the surge in defaults. They observe that both higher LTV and DSTI levels are associated with higher default probabilities, while the effect of DSTI is moderate and decreasing with initial credit quality (measured by a FICO score). In the same vein, Sherlund (2008) and Mayer *et al*. (2009) document that negative equity and a higher LTV ratio lead to more defaults on US mortgage markets. Overall, on average, the effect on default appears to be both less strong and less consistent for the DSTI ratio.

Finally, empirical evidence verifies also that the relationship between risk and lending standards may not be linear. Haughwout et al. (2008) find non-linear effects of LTV and DTI in default rates and Qi and Yang (2009) find nonlinearities of the LTV ratio in explaining the loss given default in the US mortgage market. Quercia *et al*. (2012) consider, among other variables, the effect of LTV at origination and debt-to-income on default. While they observe a positive impact of LTV and a positive but weak effect of debt-to-income on default risk on average, they also show that these effects may depend upon the absolute income level of borrowers. When the relationship between LTV and risk is positive for low (and very low) income borrowers, it becomes negative for intermediate income borrowers. They also observe a similar reversal for debt-to-income. This suggests that the relationship between LTV or DSTI and risk might not be monotonic. It further suggests that lenders follow different origination policies for similar values of LTV or DSTI based on different risk evaluations. Kelly *et al*. (2018) demonstrate the existence of relevant thresholds of LTV and LTI in Ireland. Kelly and O'Toole (2018) highlight the non-linear (but still increasing) relationship between LTV at origination and default rates in the UK. Nier *et al*. (2019), using Romanian data, identify also a non-monotonic relationship between DSTI on default probabilities. Other findings (Morgan *et al*., 2019, de Jong and de Veirman, 2019) confirm this heterogeneity of risk exposures across borrowers with different levels of the ratios. To summarize, these researches identify important non-linear effects of LTV and DSTI at origination in different countries.

The previous paragraphs also show that the literature analyzing the link between lending ratios and credit risk considers risk (i.e. default) at the loan level exclusively. Hence, macroprudential policies operate a conceptual link between microeconomic features of loans and macroeconomic variables such as loan supply or house prices. Nevertheless, defaults are not only driven by borrower specific risks such as health hazards or domestic events like a divorce and, they are also determined by macroeconomic driven shocks typically on income and/or house prices. Indeed, empirical evidence also highlights the systematic nature of defaults on housing loans. In that perspective, empirical studies document the role house prices are playing on the default rate when the LTV ratio is high (Avery *et al*., 1996), or the role of change in income and unemployment when the DSTI ratio is high (Johnson and Li, 2010), or the combined effects of price and income shocks (Foote et al., 2009). In addition, they show that prices shocks seem to play a predominant role relative to income shocks on the default rate. Moreover, it is well documented that lending standards are looser in expansions than in recessions (Corbae and Quintin, 2015), so that loans originated in recessions are likely riskier than those originated in expansions. In particular, the maximum LTV ratio increases during recessions, which could reduce the borrowers' capacity to reimburse their loans during bad times. In other terms, in the years prior to a recession, the borrowers' leverage tends to increase (Chen et al., 2020) what could affect lenders' solvency when the recession comes. This systematic dimension of credit risk calls for considering credit risk not only at the loan level, but also at the portfolio level, at either the lender level or the industry level. Fundamentally, what matters for the lender is the realization of numerous correlated defaults, i.e., unexpected portfolio losses, which are determined by the common sensitivity of the borrowers to systematic risk resulting from income and house prices changes[8]. In order to compute potential losses at the portfolio level, we rely upon methodologies that expand the framework underlying the Basel credit risk regulations (Gordy, 2003, Lucas *et al*., 2001). Hence, the

[8] Adverse shocks of these factors may indeed induce a wave of defaults as was the case in the U.S. subprime market, when real interest rates rose and housing prices dropped sharply (Mayer, Pence, and Sherlund, 2009).

regulation of LTV and/or DSTI ratios may have an impact on the portfolio total risk by changing the composition of the pool of borrowers, not only in terms of the borrowers' PDs and LGDs, but also in terms of the dependence structure across specific groups of borrowers, identified from their LTV or DSTI levels.

3. Data: Changes in lending standards, defaults, and losses in the French housing loans market

This paper uses a proprietary database of French housing loans provided by a main guarantor of the French housing loans market. The dataset contains more than 2.2 million loans records originated from 2000 to 2016 and whose default histories are recorded over the 2000-2019 period[9]. It retains only housing loans which destination is to finance home ownership, those for which the issue of the sensitivity to income shocks is relevant. It also excludes loans resulting from loan repurchases as well as bridge loans[10]. Most loans are standard amortizing loans with fixed rate, the very dominant form on the French market in the period under review. Overall, loans in our database amount to 338 billion euros[11].

The database provides information about loans characteristics at origination (date of origination, amount, maturity, type of interest rate, type of loans, regulated or not, loan-to-value and loan-to-income ratios) and about borrowers' characteristics at the origination (age, marital status, number of children, profession, income, real estate wealth and wealth hold in financial assets). The database provides also ratings at origination using a four non-default grades rating scale. The dataset contains the complete history of loans in default in the dataset (date of default, remaining capital due at the entry of default. The history of defaults allows distinguishing between two types of defaults. The first type of default is the conventional Basel 2 default (90 days past due). However, once a default occurs, a restructuring process involving the lender and the borrower determines if a restructuration is feasible. In that case, the loan is still alive and default is not an absorbing state. If restructuration

[9] Each record comprises borrowers' credit files containing one or several loans contracted between 2000 and 2017. Indeed, borrowers contract on average approximately two loans. For convenience, we denote as a loan the entire debt funding taken on by the household in order to acquire its home. Actually, this debt can be the aggregation of several loans (typically two), common combinations being a fixed and a variable rate or a regular bank loan combined with a state-subsidized loan.

[10] Repurchases of loans were frequent in the 2010s in France, due to the context of decreasing rate of interest. In our database, they represent 22.4% of the initial database over the period under study (i.e. 666.320 loans). Bridge loans were also excluded due to their specific status which appears to favor the realization of more defaults than the ordinarily loans. There were 150.245 bridge loans in our database over the period under study.

[11] Which represents more than one third of the production of loans for home ownership for the period, according to the ACPR-Banque de France (2021) survey.

appears impossible, the restructuration process ends with a closeout, generally leading to the seizure of the estate. Hence, a loan may default several times over its lifespan[12]. Moreover, we assume that losses occur only in the case of defaults, which corresponds to observation when neglecting the administrative costs of the restructuration. Our database contains 40.904 defaults over the 2000-2019 period, of which about 58.1% were solved by a return to a sound situation before one year. For each closeout default with a definitively closed recovery process[13], the dataset provides information about the rate of recovery, which allows determining the Losses Given Default (LGD). Thus, effective losses come from borrowers that represented 35.8% of the population in default. For this population, the average rate of LGD reaches 31.0% and the burden of all losses for the guarantor over the period amounted to 472 million euros[14].

Until 2019, the French market for housing loans was characterized by the absence of any explicit regulation of lending standards i.e., caps neither on LTV nor DSTI. Therefore, the actual relationships between prices, lending standards, and credit risk reflect the lending policies and risk management decisions of French banks, given the characteristics of the households credit demand. Figure 1 shows the changes in house prices, LTV, and DSTI at origination in our data from 2000 to 2020. It first underlines the sharp growth of prices and lending standards in the 2000s until the outbreak of the Great Financial Crisis (GFC) in 2008. The GFC is associated to a joint drop of the three variables followed by a rapid rebound. In the years immediately following the GFC (2010-2013), Figure 1 shows that the three variables are (on average) stable. However, after 2013-2014, the growth of house prices and LTV ratios picks up, while DSTI remain overly stable.

Thus, while the three variables appear to be closely linked until the mid-2010s, DSTI ratios are from then apparently disconnected from prices and LTVs. Grounding on these observations, we distinguish four vintages of loans:

i. the 2000-2004 vintage, characterized by the beginning of a strong growth of the French loans production,

[12] However, the timespan between two default events for a same loan is highly variables, within one quarter (the observation frequency in the data) to several years. For the sake of simplicity, we consider two consecutive defaults occurring within one year as a single default.

[13] The recovery process often lasts several years. Due to the regulatory discounting rules in the determination of expected recoveries, the duration of recovery turns out to be a first order determinant of regulatory capital. We neglect this issue in the present study.

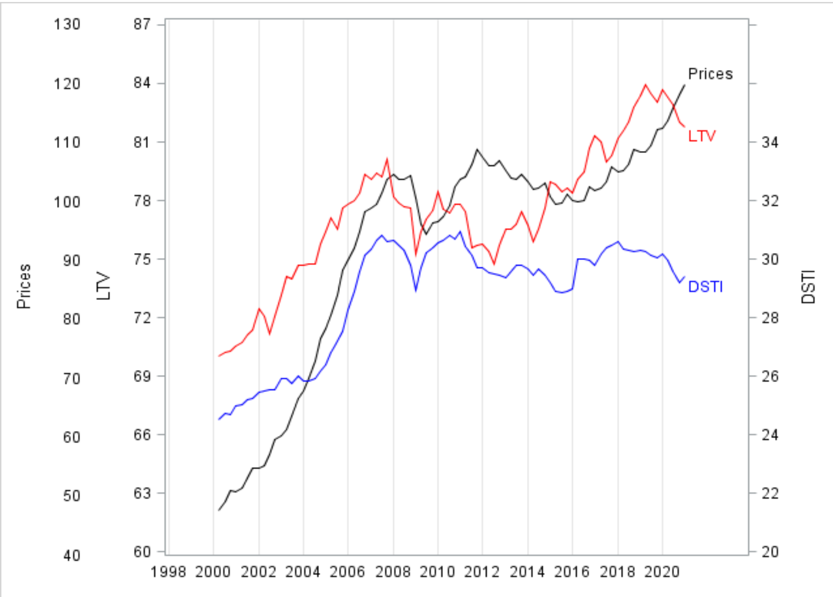
[14] In our paper, we retain an 'accounting' definition of losses, which excludes overhead and structure costs and discounting of recovery flows, but includes the costs of recovery. This definition differs from the regulatory one, which includes structure costs and discounting of recovery flows.

ii. the 2005-2008Q2 vintage, also marked by the pursuit of the loans growth but also by a relaxation of lending standards,

iii. the 2008Q3-2012 vintage, where the lending policies were hurt by the GFC and the following Eurozone crisis,

iv. the 2013-2016 vintage where lenders have still to bring responses to a growing demand of loans, partially inflated by the housing prices growth, while controlling their lending standards relative to those of the pre-crisis vintages.

Figure 1: Changes in house prices, lending standards at origination - 2000 to 2019



At this stage, it is useful to present the cross distribution of the housing loans portfolios in four classes of DSTI and LTV levels. The definition of the ratios classes aims at distinguish moderate and high or very high levels of each ratio. For the DSTI ratio, the classes are: a) less than 25%, b) 25%-30%, c) 30%-35% and d) equal or higher to 35%. For the LTV ratio, the classes are: a) less than 80%, b) 80%-90%, c) 90%-100% and d) equal or higher to 100%. Table 1 shows how the two ratios interacted during the period under review. It displays, by vintage of origination, the distribution of exposures by LTV and DSTI levels in the total population of loans. It shows that the main change in the distribution of the loans portfolios intervened during the vintage preceding the GFC, where the share of loans with the highest levels of LTV (with no down payment) and DSTI (equal or larger than 35%) increased substantially. Indeed, the share of loans with no down payment increased from 15% to around 25% in the population. In addition, the share of the higher segment of DSTI climbs to at the same time to more than 20%. These shares have been maintained at that level in the following vintages. On the one hand, these features reflect the relaxation of credit standards just before the GFC. On the other hand, the stability of the shares at high levels in the period after reflects the adjustment of bank loan policies to the strong and continuous growth of house prices in the 2010s in France. Thus, house price growth has resulted in a significant growth of the borrowing constraints for a large proportion of households.

Table 1: Loan production across DSTI and LTV classes, by vintages (in %)

vintage 2000 - 2004					
	DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35	all
LTV<=80	27.57	12.02	8.51	5.28	53.38
80<LTV<=90	6.06	4.54	3.42	1.96	15.99
90<LTV<100	5.66	4.56	3.41	1.92	15.55
LTV=>100	5.65	4.19	3.13	2.11	15.08
all	44.93	25.31	18.48	11.28	100.00
vintage 2005 - 2008Q2					
	DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35	all
LTV<=80	17.81	9.96	8.47	7.89	44.13
80<LTV<=90	4.25	3.72	3.53	3.11	14.61
90<LTV<100	4.65	4.62	4.56	4.02	17.84
LTV=>100	6.33	5.47	5.38	6.23	23.42
all	33.04	23.76	21.94	21.25	100.00
vintage 2008Q3 2012					
	DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35	all
LTV<=80	15.37	10.01	9.21	9.30	43.88
80<LTV<=90	3.19	3.56	3.80	3.50	14.05
90<LTV<100	3.87	5.05	5.59	4.77	19.29
LTV=>100	4.79	5.89	6.10	6.00	22.78
All	27.22	24.51	24.69	23.58	100.00
vintage 20012 - 2016					
	DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35	all
LTV<=80	15.94	9.50	7.99	7.39	40.82
80<LTV<=90	3.80	3.99	3.65	3.34	14.78
90<LTV<100	4.92	5.87	5.47	4.98	21.24
LTV=>100	5.98	6.52	5.63	5.03	23.16
all	30.65	25.87	22.75	20.73	100.00

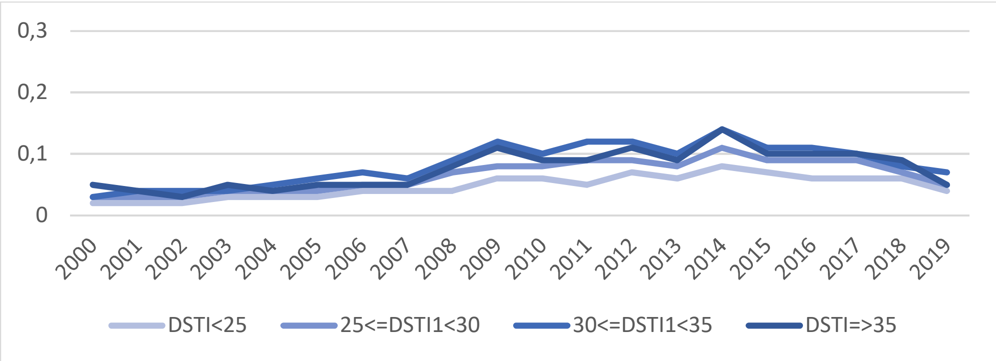
Table 1 displays the share (in percent) of each DSTI crossing LTV bucket in the total population of loans. Thus, the share of the segment grouping both higher LTV and DSTI tranches reaches 6.2% of the total loans in the second vintage starting in 2005, before the financial crisis.

These changes came along with changes in default rates. Panels A and B in Figure 2 present the annual default rates (closeout default) by DSTI and LTV classes, respectively. They show an increase of the default rate with the LTV level, but a relative proximity of the default rate in the two upper DSTI classes.

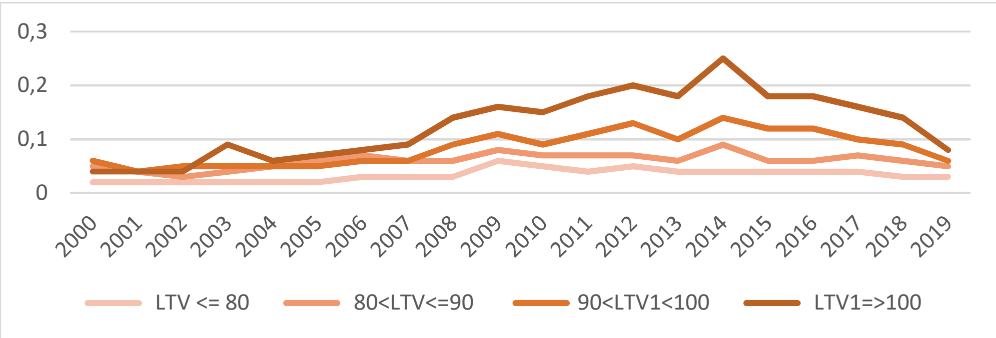
Figure 2 also shows clearly that the default rate reaches their higher levels in the upper class of the LTV ratio.

Figure 2: Annual default rates (in %) by DSTI and LTV levels 2000 – 2019

Panel A / by DSTI level



Panel B / by LTV level



Notice that the 2014 peak corresponds to changes in the risk class of loans because of the Asset Quality Review implanted by the EBC when it became in charge of the banking regulation.

Table 2 completes the risk picture by displaying the average Loss Given Default (LGD) rate across LTV and DSTI segments. It shows clearly that borrowers with the higher LTV ratios at origination (equal to or higher than 100%) have the highest rates of LGD especially in the vintage preceding and following the great financial crisis. On the contrary, the value of the LGD rate is slightly higher in lower segments of the DSTI ratio and remains quite stable in the mid- and upper segments during the last three vintages.

Table 2 Average values of LGD by LTV and DSTI segments

A/ DSTI segmentation

vintage	DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35
2000-2004	0.25	0.23	0.23	0.23
2005-2008Q2	0.43	0.49	0.34	0.28
2008Q3-2012	0.38	0.51	0.33	0.27
2023-2016	0.30	0.24	0.29	0.21

Table 2 (continued)

B/ LTV segmentation

vintage	LTV <= 80	80<LTV<=90	90<LTV<100	LTV=>100
2000-2004	0.19	0.23	0.23	0.29
2005-2008Q2	0.20	0.29	0.30	0.52
2008Q3-2012	0.23	0.24	0.31	0.47
2023-2016	0.14	0.21	0.29	0.29

4. The characterization of defaults of high-DSTI and high-LTV loans

In this section, we investigate the relationships between DSTI (resp. LTV) at origination and default. We proceed in two steps. First, we characterize defaults using a set of characteristics of acquiring households, acquisitions, and their loans, excluding DSTI and LTV. The estimated parameters allow computing the expected default probability at the loan level. In the second step, we analyze the relationships between these expected probabilities of default and DSTI and LTV at origination, respectively. Indeed, lending standards are assumed to synthesize the constraints and risk factors borrowers are exposed to. Accordingly, their use as the unique instrument (or in combination) of macroprudential policies reflect the implicit assumption that they reflect, if not entirely, at least mostly the available information about the risk exposure of borrowers. Hence, rather than modelling the quite straightforward and expected effect of larger DSTI or LTV levels on the likelihood of default, we investigate the differences across DSTI and LTV levels of default probabilities modelled from a set of characteristics expected to be captured besides by DSTI and LTV.

Modelling default

Hence, we assume that the set of explanatory factors x_i is linked to the borrower's annual probability of default (PD) according to the logistic distribution. Hence:

$$Prob(DEF_{it} = 1|x_i) = \frac{exp(\delta x_i)}{1 + exp(\delta x_i)} \quad (1)$$

In modelling defaults, we restrict our analyses to characteristics of loans and borrowers as observed at origination. Hence, we longitudinally follow borrowers with an annual frequency as long as the operation remains alive, i.e. there is no default[15], or the loan is fully repaid, or it is repurchased by

[15] As we use Basel defaults, default is not necessarily an absorbing state. Actually, about half of these defaulting loans are successfully restructured. Hence, multiple defaults of a given loan are possible.

another bank. Considering the PD over a finite (annual) time horizon rather than over its entire lifespan, i.e., preferring incidence to prevalence, limits the impact of right-censorship of the data. Moreover, restricting data to loans originated prior to 2017 but recording defaults until then end of 2019 (i.e., until the outbreak of Covid-19, which froze out defaults on many segments of the credit market) takes into account the common observation that defaults are generally rare in the time just after origination. In other words, it takes some time until the borrower's solvency substantially evolves given its initial state at origination, as for instance captured by a credit rating[16].

Moreover, the successive states of each operation (either alive or default) may be correlated over time, reflecting the possible clustering due to the repetition of measurement over the same subjects over time. Accordingly, we use generalized estimating equations (GEE) (Liang and Zeger, 1986) with an order-1 auto-regressive correlation structure defined as:

$$Corr(DEF_{it}; DEF_{it-j}) = \alpha^j \text{ , } j = 0,1,2,\ldots,t-1$$

We introduce first the profession of the main borrower.[17] Besides income, the nature of the profession may convey information about the borrower's exposure to income shocks. While civil servants may be widely insulated from income shocks, artisans, professionals, or shopkeepers may be more exposed. Moreover, the profession may reflect resource allocation choices determining the characteristics of loans in terms of DSTI or LTV. Hence, owners of personal affairs may prefer keeping precautionary savings either to absorb activity shocks or to take advantage of unexpected investment opportunities rather than investing in their home acquisition, therefore increasing their LTV, all things being equal. More precisely, we consider 16 professions (see Table A-1 in the appendix for definitions), using managing civil servants as the reference category. We also consider the civil status, using married couples as the reference category. The civil status may reflect some of the financial constraints of the borrowers. For instance, a divorced individual may face specific financial obligations. We also consider the number of children (childless households as a reference), which can be expected to be directly linked to the expenses of the household. Finally, we consider the borrower's age (or the average age in case of a couple) as the likelihood to face a health-driven shock may increase with age, determining the features of the loan in terms of DSTI and LTV and, ultimately, default risk. We also consider some financial characteristics starting with annual income as an obvious control variable. In addition, we introduce the rate of financial assets defined as the amount of financial assets over the borrowed

[16] This intuition underpins the maturity adjustment entering the computation of regulatory capital requirements in the Internal Ratings Based (IRB) framework of credit risk (BCBS, 2006).
[17] For couples, lenders identify a main and a secondary borrower. Generally, the main borrower has the highest income, reflecting the economic inequalities within households. Here, in order to avoid having to consider pairs of professions, we make the simplifying assumption that the profession of the main borrower is representative of the household's exposure to income shocks.

amount. We expect that households holding more financial assets may choose to take from their savings to reduce DSTI or LTV at origination. We also consider the presence of previous real estate by creating a binary variable equal to 1 if the household has a positive real estate in its patrimony previously to the acquisition and 0 else. This variable provides a proxy to identify first homebuyers, which may face tighter financial constraints. Finally, we consider the level of preexisting debt of the household, which explicitly enters the regulatory definition of the DSTI and the derived cap. As an additional borrower characteristic, we introduce the length of the banking relationship with the lender. Indeed, the French market for housing loans is highly competitive as housing loans are expected to bind the borrowers with the lending bank, providing opportunities for future sales of financial services over the long run[18]. As a last set of control variables, we consider the value of the acquired real estate, the initial length of the loan, and, as a broad geographic control, a binary variable equal to 1 if the real estate is located in the Parisian region and 0 else, in order to reflect the higher real estate prices in this specific area. However, we exclude both LTV and DSTI from the determinants of default although, as shown in the literature review, both are likely associated to the likelihood of default. This ex ante exclusion relates to our research design, which analyzes estimated default probabilities in terms of LTV and DSTI. Table 3 gathers the estimation results.

The overall fit is correct, although not very high, with an area under curve slightly larger than 71%. Indeed, results from the recent literature on default prediction often display values about 80% on average (see, e.g. Barbalia *et al*., 2021). However, these studies often control for economic changes over time. Here, we chose not to control for economic changes over time, neither through the introduction of macroeconomic variables nor through the introduction of time effects (fixed or random). Our purpose is not to forecast defaults according to some economic scenario or path given the loans characteristics. As macroprudential policies consider lending standards at origination, we measure their average link with default probabilities in a through-the-cycle manner, i.e. unconditionally to economic conditions. This nevertheless requires that the data cover sufficiently diverse economic conditions to provide robust estimates of the link between characteristics of households and loans at origination and defaults over time. As our data include the 2008 and 2012 shocks, we consider this condition as fulfilled.

[18] Additionally, banks compete to attract new clients by repurchasing housing loans from the initial lender. Although we do not consider loan repurchases in our analyses, they represent 21% of the total loans of our initial data.

Table 3 Default model

	[1]
Age	0.0004***
Income	0.0001***
Financial assets (%)	-0.0001***
Home value	-0.0001***
Length	-0.0002***
Maturity	0.0004***
Previous debt	0.0001***
Prev. Home owner	0.813***
Occupation (ref="Managers, public sector")	
Employees, public sector	1.570***
Unemployed	2.255***
Students	1.029
Retired	2.264***
Without activity	3.397***
Artisans and shopkeepers	4.517***
Farmers	2.978***
Executives	4.032***
Professionals	3.353***
Professionals (health)	1.778***
Other professionals	2.414***
Workers	1.689***
Managers, private sector	1.497***
Employees, private sector	2.204***
Temporary workers	2.001***
Civil status (ref= "Married couple")	
Single woman divorced	0.949
Single woman	0.968
Single man divorced	1.623***
Single man	1.736***
Couple	0.806***
Couple w/ divorced partner	1.120***
Other	0.855***
Children (ref=0)	
1	1.265***
2	1.411***
3	2.176***
4 +	2.488***
Parisian region	1.121***
QIC	402,102
AR(1)	0.022
AUC	0.714
N obs.	15,363,282

Table 3 displays average marginal effects for continuous variables (see definitions in Table A.1 in the Appendix) and odds ratios relative to the reference for categorical variables. ***,**,* denote p-values of the parameter estimates at the 1%, 5%, 10% level, respectively.

Variables reflecting financial constraints of borrowers actually increase default risk. Hence, the level of preexisting debt, the initial maturity of loans, as well as a lower level of financial assets are positively associated to a higher default likelihood[19]. Similarly, preexisting real estate wealth, while allowing a larger borrowed amount also makes default less likely. Moreover, the length of the bank-customer relationship as a negative effect on default, reflecting the ability of lenders to gather information overtime in their decision-making, allowing identifying low risk borrowers to which lenders can issue high-DSTI or high-LTV loans. Moreover, a larger income is associated to an increase in the default probability. Nevertheless, a possible explanation could be that the effect of income on risk is dominated by the occupation fixed effects (see below), which may better reflect households' exposure to income shocks. Indeed, significance tests in Table A.4 in the Appendix show that the explanatory power of occupation dominates income. Moreover, a larger value of the acquisition decreases default risk. This could reflect the initial adjustments made by households and/or imposed by the lenders at origination. Hence, the observed effect could capture a residual wealth or income effect, where riskier and possibly less wealthy borrowers acquire less valuable homes. Thus, for actually originated loans, risky borrowers may be ex ante constrained on the borrowed amount, which may reduce the price (i.e., the characteristics) of the acquisition. An alternative explanation could be linked to a home equity effect where borrowers with more valuable homes may exert more effort to avoid default.

Turning to households characteristics, we first observe that older borrowers are more likely to default. This could reflect the health hazard related to ageing, which may affect income and repayment capacity. Then, we observe a monotonic increasing effect of the number of children on default risk. Moreover, single men appear to be on average more risky than married couples are (and in fact, more than all other modalities of civil status). Finally, all occupations turn out to be riskier than civil servants in management positions (at the noticeable and striking exception of students, which only represent 0.14% of all borrowers). Hence, irrespective of the actual level of income, occupations may indeed reflect the borrower's exposure to income shocks. For instance, we observe the highest odds ratios for artisans and shopkeepers, executives, and (non-health) professionals. All these occupations are indeed characterized by unstable, although often high revenues. Overall, the structural and occupational dimensions of borrowing households have strong and structuring effects on default risk.

[19] The average marginal effects shown in Table 4, given the chosen marginal changes, have to be compared to the average annual default rate of 0.0019 observed in the data.

Analysis of estimated default probabilities in terms of DSTI and LTV.

Using the parameter estimates $\hat{\delta}$ from Equation (1), we compute the estimated default probability of each loan given its characteristics x_i:

$$\widehat{PD}_i = \frac{exp(\hat{\delta}x_i)}{1 + exp(\hat{\delta}x_i)} \quad (2)$$

This allows analyzing the link between lending standards and our estimated PDs. More precisely, in order to limit the heterogeneity generally observed in individual data, we compute the average estimated PD for each percentile of the distributions of LTV and DSTI, respectively.

Figure 3 Estimated PD as a function of LTV at origination

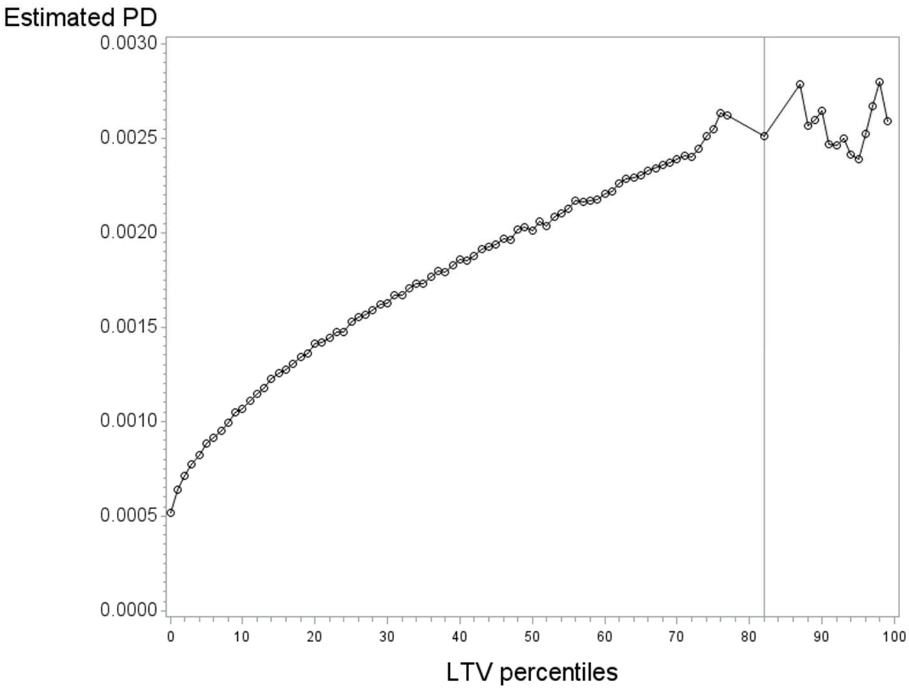


Figure 3 plots the average estimated default probability per percentile of the distribution of the loan-to-value ratio at origination. The vertical reference line corresponds to a LTV equal or larger than 100%. Over the entire period, loans with a LTV equal or larger than 100% represent about 18% of originated loans.

Figure 3 (resp. 4) shows the resulting curve for LTV (resp. DSTI). Both curves are broadly increasing, reflecting the common observation that higher values of LTV and DSTI are on average associated to higher average PDs. However, when looking more closely, the two curves have differing patterns. First, the association between LTV and estimated PD is very close (the correlation coefficient between the two variables is 96.7%) and nearly linear. It only slightly decreases for loans with a LTV between 103%

and 106%[20]. This decrease could reflect some heterogeneity of these loans, with some risky loans besides low risk loans, for which the absence of down payment may not be an issue. Second, while overall increasing, the DSTI-PD relationship turns out to be increasing until a DSTI of about 30%, where it becomes flat with an additional peak around 45%.

Figure 4 Estimated PD as a function of DSTI at origination

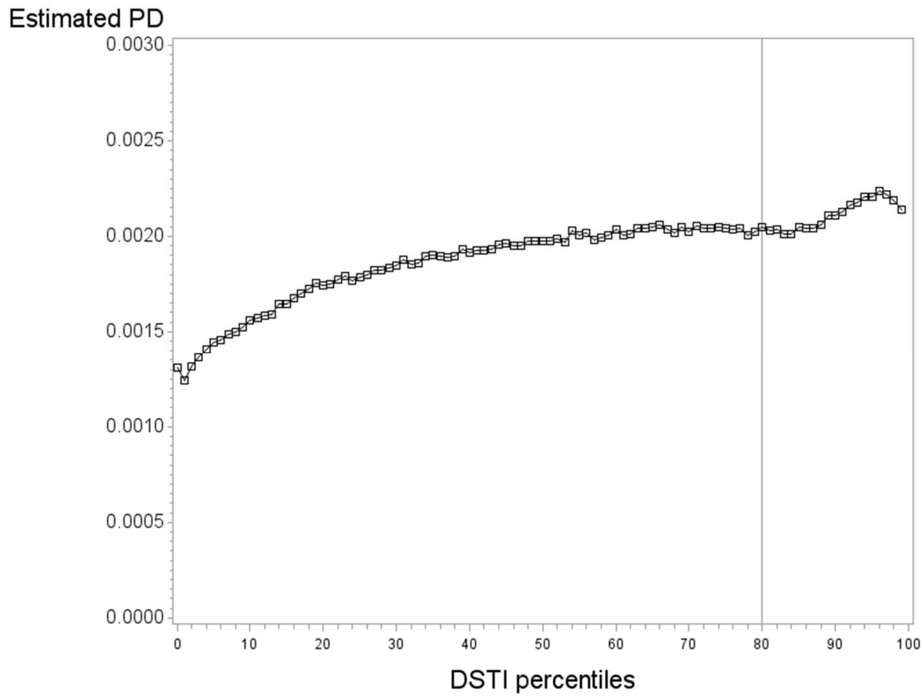


Figure 4 plots the average estimated default probability per percentile of the distribution of the debt-service-to-income ratio at origination. The vertical reference line corresponds to a DSTI equal to 35%.

So far, our results are consistent with available evidence: A larger LTV is closely associated to a larger default likelihood while the DSTI-PD relationship is less clear-cut. This indeed questions the ability of DSTI to characterize the riskier loans and therefore to control the overall risk of housing loans. However, despite the differences suggested by Figures 3 and 4, both indicators are highly and positively associated to default risk. Thus, although potentially less precise than LTV, DSTI could nevertheless provide a relevant policy instrument in curbing both the individual risk of borrowers and the overall risk of housing loans. To address this issue, we reconsider the DSTI-PD relationship while distinguishing between loans with down payment (i.e., with a LTV strictly lower than 100%) from loans without. Indeed, despite the positive association between lending standards, the descriptive statistics shown in Section 3 (Table 1) clearly show that high-LTV loans (i.e., without down payment) represent

[20] Loans with an LTV at origination larger than 100% mainly correspond to the situation where, besides the absence of a down payment, the loan also covers taxes and/or works to be done in the acquired real estate.

a sizeable share of loans at all DSTI levels. Hence, computing the average default probability of high-LTV loans conditional at the DSTI-percentile level could provide additional insights about the ability of DSTI alone to characterize risky loans.

Figure 5 Estimated PD as a function of DSTI at origination, conditional to down payment

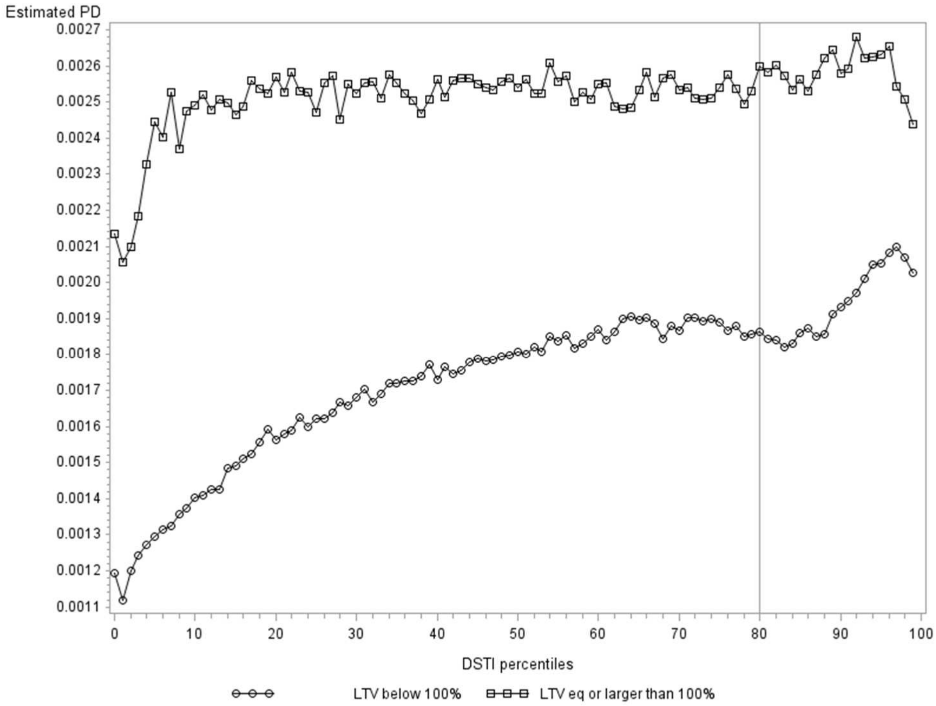


Figure 5 plots average estimated PD per percentiles of DSTI conditional to the existence of a down payment. The vertical reference line corresponds to a DSTI equal to 35%.

Expanding Figure 4, Figure 5 plots the average predicted PD at the DSTI percentile level distinguishing loans according to the existence of a down payment or not. First, Figure 5 confirms that high-LTV loans appear to be on average riskier at all DSTI levels. Second, and more importantly, the average estimated PD of high-LTV loans turns out to be merely independent from their DSTI. More specifically, we observe a merely flat curve for high-LTV loans at the exception of loans with very low and very high DSTI levels. Indeed, when excluding loans in the first and last DSTI deciles, the slope of an OLS regression between the average $\widehat{PD}_i$ and percentiles is about $5.7.10^{-7}$ (t-stat 3.29). Although statistically significant, the economic effect turns out to be virtually immaterial, amounting to an increase in the average predicted PD of only $4.5.10^{-5}$ between the boundaries of the first and last DSTI deciles. This suggests that the DSTI-default relationship, already weaker than the LTV-default relationship, could even become weaker when considering loans with low or no down payment.

Moreover, these results remain qualitatively unchanged when considering separately the four vintages defined in Section 3. Overall, loans with no down payment are indeed riskier, as observed in our descriptive statistics and widely confirmed by previous research, but their risk, measured be their estimated PD, appears to be largely independent from their DSTI. This actually casts doubts about the ability of DSTI on its own to identify the riskier loans within the entire population of housing loans. Indeed, in our (large and representative) sample, no down payment loans with an initial DSTI level below the regulatory limit of 35% represent more than three-quarters (76.5%) of all no down payment loans. Hence, the regulatory DSTI cap misses the main part of high-risk loans originated on the French market. This potentially limits the ability of a single DSTI cap to curb the overall risk of the lenders' portfolios.

5. The interdependence between LTV and DSTI, and its implication for risk identification

The previous results suggest that DSTI may be less efficient in identifying riskier loans than LTV, although both are, on average, clearly associated to default risk. In this section, we test a possible explanation for the observed difference. We investigate whether DSTI ratios may be to some extent managed in order to reconcile, on the one hand, higher loan amounts resulting from increasing house prices and, on the other hand, the willingness of lenders to limit excessive DSTI levels. More precisely, we assume the existence of a partial substitution between LTV and DSTI ratios, at least for some borrowers. Indeed, growing house prices lead households and lenders to increase borrowing, all things being equal, overall increasing their financial constraints and their risk. As lending increases, we first expect LTV ratios to overall increase, increasing default risk as shown in the previous section. At the same time, one may also expect increasing DSTI levels. However, altering the characteristics of loans may help to limit the increase of DSTI in order to make the loan sustainable and acceptable, with respect to some, possibly implicit, norm. Typically, increasing the maturity of loans, decreasing the value (hence the features) of the acquisition may limit the increase in DSTI as lending nevertheless expands. This may lead to situations where, at least for some borrowers, LTV levels increase while DSTI level remain stable or even decrease. However, as some high-LTV borrowers may remain low to moderate-DSTI borrowers, the average PD of low- (resp. high-) DSTI loans increases (decreases), weakening the DSTI-PD relationship relative to the LTV-PD relationship. This mechanism could explain the apparent disconnection between LTV and DSTI average levels from 2012 onwards (see Figure 1). While the two average ratios moved together until the GFC, LTV levels increased again from 2012 while the DSTI remained overly stable (again on average) at the same time.

In order to address this issue, we need a framework that takes into account a possible heterogeneous interdependence between LTV and DSTI ratios. More precisely, we consider the interaction between the likelihood of high-LTV loans to be also high-DSTI loans. This requires definitions of these two types of loans. Here, we use two straightforward, although conceptually different definitions. Considering first debt-service-to-income, we simply use the regulatory limit of 35%, which, in France, includes the preexisting debt of the borrowing household. This choice is straightforward as it aims at describing the features of borrowing households considered as excessively risky by the French regulator. For loan-to-value, in the absence of any domestic regulatory guidance, we define high-LTV loans as loans with no down payment. First, as shown in Section 3, these loans represent a sizeable share of housing loans, reflecting a common practice of lenders. Second, France is the country in the European Union with the highest average LTV at origination, about 88% over the period 2016-2018 (Lang et al., 2020). Thus, choosing a limit of e.g. 90% is likely to discriminate only weakly risky loans within the entire population. Moreover, the inability to provide any down payment is likely to reflect the financial constraints faced by borrowing households.

Th interdependence between high LTV and high DSTI values may result from several channels. First, both lending standards may be determined by a set of common factors acting in the same or in opposite directions, such as income, wealth, occupation… Moreover, some additional unobserved but possibly correlated factors may also imply some interdependence. Therefore, they may share to some extent common observed and non-observed explanatory factors. Hence, the probabilities of a new loan to be high-LTV and high-DSTI are determined jointly. In order to assess the existence of such an interdependence, we estimate first a bivariate probit (BP) model specified as the following system of two equations:

$$\begin{cases} LTV_i^* = \gamma' x_i + \xi_i \,, LTV_i = 1 \; if \; LTV_i^* \geq 100\%, LTV_i = 0 \; otherwise \\ DSTI_i^* = \delta' x_i + \upsilon_i \,, DSTI_i = 1 \; if \; DSTI_i^* \geq 35\%, DSTI_i = 0 \; otherwise \end{cases}$$

$$[\upsilon_i, \xi_i] \sim \Phi_2[(0,0), (1,1), \rho], \rho \in [-1,1]$$

As explanatory factors, we consider the same set of households' characteristics use in the default model of the preceding section. Due to computational constraints, the BP model (as well as all models in this section) is estimated on a 10% sample of the data. The random sample is stratified in order to replicate the proportions of high-LTV and high-DSTI loans within the complete data. Results are gathered in Table 4.

Table 4 Estimation results, bivariate probit model

	[1]	[2]
	DSTI ≥ 35%	LTV ≥ 100%
Age	-0,00157***	0,00067***
Income	-0,00458***	-0,00018***
Financial assets (%)	-0,03095***	-0,03199***
Home value	0,00045***	-0,00008***
Length	0,00000***	0,00000***
Maturity	0,00080***	0,00077***
Previous debt	0,02592***	0,00433***
Prev. Home owner	1,37644***	1,86116***
Occupation (ref="Managers, public sector")		
Employees, public sector	0,9342***	1,7291***
Unemployed	0,9827	1,1679***
Students	0,8588***	0,8096***
Retired	1,1145***	1,4372***
Without activity	1,1073***	1,0991***
Artisans and shopkeepers	1,2493***	0,9049***
Farmers	1,2634***	0,7696***
Executives	1,1180***	1,1377***
Professionals	1,0151	1,1049***
Professionals (health)	1,0683**	1,0247**
Other professionals	0,7062***	0,5806***
Workers	0,8683***	0,9769***
Managers, private sector	0,9759***	1,0599***
Employees, private sector	0,9469***	1,4343***
Temporary workers	0,9320***	1,0529***
Civil status (ref= "Married couple")		
Single woman divorced	1,2778***	0,8578***
Single woman	1,7512***	0,791***
Single man divorced	2,1365***	0,8653
Single man	1.6742***	0,9594***
Couple	1,0261**	1,1033***
Couple w/ divorced partner	0,9634***	0,8162***
Other	0,8720***	0,9308
Children (ref=0)		
1	0,9291***	1,1121***
2	0,8915***	1,1752***
3	0,8426***	1,1705***
4 +	0,8755***	0,9333***
Parisian region	0,9920	0,8544***
ρ	0.086***	
N Obs	201,175	

Table 4 displays average marginal effects for continuous variables (see definitions in Table A.1 in the Appendix) and odds ratios relative to the reference for categorical variables. ***,**,* denote p-values of the parameter estimates at the 1%, 5%, 10% level, respectively. Appendix A details the computation of marginal effects and odds ratios.

First, estimates show a set of common factors that may underlie the overall positive association between DSTI and LTV. Hence, a higher income and a larger share of financial (mainly financial) assets are associated to lower DSTI and LTV levels. Similarly, a larger level of previous debt increases the probability to be a high-DSTI or a high-LTV borrower. Thus, these variables reflect the liquidity constraints faced by the borrowers. In addition, high-DSTI and high-LTV loans have a longer initial maturity. Unsurprisingly, constrained borrowers may try to expand borrowing by lengthening maturity, making monthly repayments sustainable given their income constraints. Besides, a longer bank-customer relationship increases the probability to observe high lending standards loans, possibly reflecting the information gathered over time allowing lenders to identify low risk borrowers. Finally, borrowers already owning (net) real estate are much more likely to get high-DSTI or high-LTV loans. This may reflect a collateral effect. Indeed, French housing loans are strong recourse loans, leading lenders to consider the overall patrimony of borrowers in their risk assessment.

Second, we observe opposite results in equations [1] and [2] for the age and home value variables. Younger borrowers, possibly characterized by lower income and wealth levels, are more likely to be high-DSTI borrowers. However, younger borrowers are less likely to be high-LTV borrowers. These divergences may reflect differing profiles among borrowers. Older borrowers could also be wealthier but at the same time less likely to devote this wealth to the acquisition of their home, anticipating for instance a future loss in income due to retirement. Moreover, a higher value of the acquisition is positively associated to DSTI, but negatively to LTV. Thus, households acquiring estates that are more expensive may be unwilling to mobilize their existing wealth, which nevertheless remains accessible to lenders in case of default due to the strong recourse feature of these loans. On the other side, a larger acquisition cost increases the likelihood of being a high-DSTI borrower, which simply reflects their funding constraints.

Moving to the categorical variables, we first observe that the composition of the household both determines the propensity to be a high-DSTI or high-LTV borrower. Considering first the civil status, our results show that single borrowers, whatever their previous status, are both likely to be high-DSTI borrowers and to provide some down payment. This suggests that these households face constraints in their ability to access credit that the supply of a down payment does not allow to decrease monthly repayments relative to married couples (in fact to couples in general). Moreover, these effects add with the number of children. Overall, having more children decreases the share of income devoted to housing debt (relative to childless households) and decreases the likelihood to provide some down payment. Hence, the children related expenses mechanically decreases the share possibly devoted to debt repayment and also make high-LTV loans more attractive in order for these households to handle their financial constraints. While most of these effects may merely be unsurprising, the associated odds ratios are generally high, illustrating the importance of these characteristics and the type of loans (in terms of lending standards) issued by typical lenders. Finally, and quite unsurprisingly, the occupation has also sizeable effects on lending standards. As we already control for income level, the occupation fixed effects may capture its stability, i.e., potential exposure to income shocks, conditional to the lender's risk assessment and commercial goals. Relative to managers in the public sector, we indeed observe quite all possible profiles in terms of probability to be (or nor) a high-DSTI or a high-LTV borrower.

Overall, the effects of income and wealth related variables go in the same direction, consistently reflecting the financial constraints faced by households. Moreover, occupation as well as the household composition determine how borrowers adjust the lending standards of their loans given the characteristics of their acquisition. However, the results gathered in Table 4 show that LTV and DSTI both reflect the economic constraints faced by the borrowing households, although not to the same extent and with some specificities. For instance, more children decreases the probability to be a high-DSTI borrower, reflecting the budget constraints of these households. Simultaneously, it increases the probability to be a high-LTV borrower. Here, households may try to relax their constraints by expanding lending without increasing repayments, typically through an increase in maturity. This first suggests that risky (constrained) borrowers may nevertheless have a low DSTI and a high LTV.

Similar observations may apply to some occupations or some modalities of the civil status. Hence, the two lending standards may be substitutes during the adjustment process between borrowers and lenders leading to origination, especially in the absence of any regulation of LTV. Noticeably, this substitution was made possible through increasing maturities. Indeed, between 2000 and 2017, the average initial maturity we observe in our data rose from 11 to 18 years. Consequently, high DSTI levels may not systematically reflect higher constraints and default risk. Similarly, the absence of a down payment could also reflect portfolio management decisions of households, i.e., to limit the allocation of their equity to the acquisition while lenders still potentially accessing to it in case of default due to the strong recourse feature of housing loans. This may weaken the expected link between lending standards and default risk.

Finally, the estimated correlation across error terms is about 0.08 a low value, although highly statistically significant. Hence, controlling for the available characteristics, the determination of LTV and DSTI appear to be (nearly) conditionally independent or weakly positively correlated. Moreover, most (although with some noticeable exceptions) explanatory variables have similar directional effects, which mainly reflects the expected positive relationship between DSTI and LTV. However, Filippini et al. (2018) show that this apparent independence may result from a inaccurate specification between the two endogenous variables of interest (here $DSTI_i$ and LTV_i). As an alternative, they consider the Recursive Bivariate Probit (RBP) model, where one of these variables enters the RHS of the second one. Here, we assume that LTV_i enters the $DSTI_i^*$ equation:

$$\begin{cases} LTV_i^* = \gamma' x_i + \xi_i \text{ , } LTV_i = 1 \text{ } if \text{ } LTV_i^* \geq 100\%, LTV_i = 0 \text{ } otherwise \\ DSTI_i^* = \alpha LTV_i + \delta' x_i + \upsilon_i \text{ , } DSTI_i = 1 \text{ } if \text{ } DSTI_i^* \geq 35\%, DSTI_i = 0 \text{ } otherwise \end{cases}$$

$$[\upsilon_i, \xi_i] \sim \Phi_2[(0,0),(1,1),\rho], \rho \in [-1,1]$$

This model adds another dependence channel between lending standards. The chosen specification assumes that the choice of a LTV level (here in a binary sense) has some unobservable and autonomous component beyond observed determinants. This component may be behavioral to some extent. For instance, the supply of a down payment may reflect the capacity and willingness of borrowers to accumulate savings ahead of the acquisition. Accordingly, the buildup of a down payment reflects the ability of borrowers to handle successfully ex ante financial constraints similar to those that will results from the acquisition. Besides, portfolio management considerations, possibly determined by taxation, may lead borrowers to be reluctant mobilizing existing wealth to provide a down payment. Moreover, a low (or no) down payment also reflects the willingness of lenders to lend to a given household without a down payment. Hence, besides the observable characteristics of households or houses, the lack of down payment may also reflect competition across lenders, which could be less stringent in terms of LTV in order to maintain DSTI beyond a given level.

Indeed, the recursive structure of the RBP model allows considering richer interactions between LTV and DSTI ratios at origination. While we may expect to observe a positive correlation, reflecting the pressure of increasing prices, the behavior of lenders and borrowers in order to address this pressure may imply a partial disconnection between the two ratios. At the aggregate level, Figure 1 suggests indeed that the association between DSTI and LTV has changed over time. While both were highly correlated in the 2000s, the (average) DSTI has remained merely stable over the 2010s while LTVs further increased after the GFC. Hence, the progressive reduction of down payments contemporaneous with an on average stable DSTI suggests the presence of the partial substitution mechanism. Table 5 presents the main estimation results of the RBP model. Overall, parameter estimates are similar to the results of the BP model, especially when considering the continuous variables. We nevertheless observe some differences in the direction of the effects for some occupation categories.

Table 5 Estimation results, recursive bivariate model

	[1]	[2]
	DSTI ≥ 35%	LTV ≥ 100%
Age	-0,0018***	0,0006***
Income	-0,0046***	-0,0001***
Financial assets (%)	-0,0339***	-0,0305***
Home value	0,0005***	-0,0001***
Length	0,0000***	0,0000***
Maturity	0,0008***	0,0007***
Previous debt	0,0261***	0,0035***
Prev. Home owner	1,3745***	1,8771***
LTV ≥ 100% (α)	See Table 6	-
Occupation (ref="Managers, public sector")		
Employees, public sector	0,9660***	1,5640***
Unemployed	1,0179**	1,2343***
Students	1,4897***	0,7265***
Retired	1,2235***	1,3692***
Without activity	1,1177***	1,000
Artisans and shopkeepers	1,2026***	0,8195***
Farmers	1,0413***	0,8264***
Executives	1,1868***	1,0755***
Professionals	1,0519***	1,0791***
Professionals (health)	1,1569***	1,0714***
Other professionals	0,9013***	0,6312***
Workers	0,9102***	0,9466***
Managers, private sector	0,9918	0,9829
Employees, private sector	0,9685**	1,2958***
Temporary workers	0,8692***	1,0401***
Civil status (ref= "Married couple")		
Single woman divorced	1,4173***	0,8387***
Single woman	1,9683***	0,7553***
Single man divorced	2.4859***	0,8606
Single man	1.8526***	0,9236***
Couple	0,9467***	1,0616***
Couple w/ divorced partner	1,0322**	0,7754***
Other	0,8965***	0,9132
Children (ref=0)		
1	0,9079***	1,0911***
2	0,8708***	1,1694***
3	0,8289***	1,1382***
4 +	0,8349***	0,9402***
Parisian region	0,9951	1,0283**
ρ	-0.367***	
N Obs	201,175	

Table 5 displays average marginal effects for continuous variables (see definitions in Table A.1 in the Appendix) and odds ratios relative to the reference for categorical variables. ***,**,* denote p-values of the parameter estimates at the 1%, 5%, 10% level, respectively. Appendix A details the computation of marginal effects and odds ratios.

The RBP model captures the direct interdependence between the lack of a down payment on the probability to observe a high-DSTI loan. More precisely, it allows computing, at the loan level, the marginal effect $ME_i(LTV_i = 1)$ of being a high-LTV loan on the probability to be a high-DSTI loan, reflecting the recursive structure in the determination of the two lending standards:

$$ME_i(LTV_i = 1) = Prob(DSTI_i = 1|x_i, LTV_i = 1) - Prob(DSTI_i = 1|x_i, LTV_i = 0)$$
$$= \frac{\Phi_2(\gamma' x_i, \alpha + \delta' x_i, \rho)}{\Phi(\gamma' x_i)} - \frac{\Phi_2(-\gamma' x_i, \delta' x_i, -\rho)}{1 - \Phi(\gamma' x_i)}$$

In general, one would expect a positive marginal effect, reflecting the pressure of increasing borrowing on lending standards. All things being equal, increasing debt (in order to absorb the pressure of increasing house prices) would result in decreasing LTVs and increasing DSTIs. However, for at least a share of borrowers, we can imagine null or negative marginal effects, i.e. to be a high-LTV loan could be associated to a decreasing probability of being a high-DSTI borrower. This feature would affect the estimated DSTI-PD relationship relative to the LTV-PD relationship, as observed in Section 4. Indeed, as some high-LTV loans, which appear to be riskier (see Figure 5), may have a lower DSTI, the expected default probability for high-DSTI (resp. low-DSTI) loans may decrease (resp. increase). This implies a decrease in the slope of the DSTI-PD relationship, given the underlying LTV-PD relationship. Considering the distribution of marginal effects $ME_i(LTV_i = 1)$ provides insights about the possible magnitude of this effect. Moreover, this substitution effect may not be homogeneous across borrowers. For instance, it could be stronger for more ex ante constrained borrowers, i.e. households less able to provide a down payment or living in areas where house prices are structurally higher. These borrowers may tend to exploit more intensively the possibility to lengthen maturity. In order to test this assumption, we replicate the RPB using varying definitions of the high-LTV loans, i.e. by considering increasing LTV thresholds from 85% to 100% (the benchmark).

Table 6 Estimation results, RBP models

	κ = 100%	κ = 95%	κ = 92.5%	κ = 90%	κ = 85%
Panel A Parameter estimates					
α	0.86***	0.59***	0.75***	0.013	0.034***
ρ	-0.36***	-0.36***	-0.45***	0.003	-0.14**
Panel B Marginal effects statistics					
Av. mg. effect (%)	2.68	-0.03	0.22	0.40	1.21
Mg. Effect ≤ 0 (%)	23.3	48.7	38.7	0.01	1.71

Panel A of Table 6 shows the parameter estimate α associated to the high LTV dummy at level κ and the correlation ρ across error terms in the RPB models across LTV thresholds κ. Panel B shows the average marginal effect and the share of zero or negative marginal effects across the sample. ***,**,* denote p-values lower than, respectively, 1%, 5%, 10%.

Table 6 shows the results of these additional estimations concentrating on the effect of LTV on DSTI and the correlation across error terms across several thresholds defining high LTV loans. Table 6 first shows that the correlation across error terms takes values that are more important (in absolute value) for LTVs larger than 92.5% while remaining close to zero for lower thresholds. However, the average marginal effect is not evolving monotonically with the LTV thresholds. Nevertheless, the share of negative marginal effects, while null or near to zero for LTVs below 90%, represents nearly half of marginal effects for LTVs larger than 92.5% and 95%, declining to one quarter for loans with no down payment. Hence, although non-monotonic, the substitution effect between high-LTV and high-DSTI is more pronounced for loans with very low or no down payments.

However, while we assume that a high LTV directly determines the likelihood to be a high-DSTI loan, the reverse could also be true. Therefore, we estimate the reverse model where $DSTI_i$ enters the LTV_i equation. Table 7 shows the main parameters of interest allowing the comparison with our benchmark model. First, we observe a positive and significant effect of a high (i.e. over 35%) DSTI on the probability to be a high-LTV loan, considering the 100% benchmark threshold. This is again consistent with the expected positive relationship between the two lending standards. In addition, this positive coefficient shows that the variables determining $DSTI_i$ (and entering the LTV_i equation) do not fully characterize the likelihood to be a high-DSTI borrower. However, controlling for $DSTI_i$, the two variables appear to be independent, the correlation being close to zero and statistically non-significant (see Table 7).

Table 7 Marginal effects of $DSTI_i = 1$ on $Prob(LTV_i = 1)$

	DSTI ≥ 35%
Panel A Parameter estimates	
α	0.19***
ρ	-0.022
Panel B Marginal effects statistics	
Av. mg. effect (%)	2.93
Mg. Effect ≤ 0 (%)	0.14

Panel A of Table 7 shows the parameter estimate α associated to the high DSTI dummy and the correlation ρ across error terms for a RPB model with an endogenous DSTI dummy. Panel B shows the mean of marginal effects $Prob(LTV_i = 1|x_i, DSTI_i = 1) - Prob(LTV_i = 1|x_i, DSTI_i = 0)$ and the share of zero or negative marginal effects across the sample. ***,**,* denote p-values lower than, respectively, 1%, 5%, 10%.

Finally, while the average marginal effect turns out to be positive (nearly 3%), nearly all individual marginal effects are positive. We draw two main conclusions from the comparison of the two specifications. First, it confirms the average positive association between LTV and DSTI as well in cross-section as over time, which may simply reflect increasing debt amounts. Second, the recursive relationship between lending standards is confirmed statistically. Indeed, when controlling for the effect of DSTI on LTV, both (binary) variables are conditionally independent. On the contrary, when controlling for the effect of LTV on DSTI, they are (conditionally) negatively correlated. This asymmetry reflects the degree of freedom a higher LTV offers in limiting the pressure on DSTI (mainly through increasing maturities and lower acquisition prices), while there is no clear motivation for a borrower to increase down payment through an increase of the weight of debt repayment, again in a context of rising prices and expending borrowing.

6. Measuring the portfolio risk of housing loans

In this section, we adopt the perspective of the lender. What matters the most for the lenders' solvency is likely the risk of a wave of correlated defaults. It comes from the exposure of segments of borrowers with identical characteristics to common systematic risk factors whose unfavorable realizations potentially create correlated defaults. In case of macroeconomic shocks, such as income or house prices shocks, borrowers could default simultaneously, leading to a potential concentration of defaults. This approach is also that of the Basel 2/3 banking regulation (Gordy, 2003) that highlights the risk of lenders' solvency deterioration coming from portfolio concentration[21]. Thus, in this paper, we borrow the asymptotic systematic risk model used by the banking regulator to calibrate regulatory capital requirements and we adapt it to highlight the differences in the risk level of loans with different levels of their LTV and DSTI ratios.

Methodology

The methodology we use consists to measure the economic capital, defined as is the capital required to absorb the lenders' unexpected losses on their portfolios at a certain horizon and with a certain degree of confidence. This methodology relies on the credit risk structural approach *à la Merton* (1974) in which the main source of credit risk comes from the borrowers' exposure to common systematic risk factors and total losses L come from the realization of the systematic risk factors alone. Formally, in this approach, defining LGD_i as the loss given default of borrower i, Y_i as a default indicator variable (equal to 1 if there is a default and 0 otherwise), and s as the realization of a set of systematic risk factors, for on a portfolio of n loans, L is equal to the expected losses conditional on s:

[21] The credit concentration risk associated to the heterogeneity of borrowers has been documented for housing loans (Jimenez and Mencia, 2009, Dietsch and Petey, 2015).

$$L = \sum_{i=1}^{n} LGD_i Y_i \ = E[L|s]$$

To compute L, we use an asymptotic credit risk model as defined in Lucas *et al.* (2001). In this model, the financial health of borrower i is represented by a latent variable U_i, whose level is determined by the realizations of the systematic risk factors. The borrower default when this level cross a threshold that determines the default. This threshold is calibrated by using the empirical probability of default $\bar{p}_j$ and defined by $\Phi^{-1}(\bar{p}_j)$, with Φ the standard normal cdf.

However, we do not compute sensitivities to the systematic risk factors at the individual level. Instead, we use a common assumption that obligors who belong to the same rating grade - on a scale of J grades - share the same sensitivity to the risk factor, represented in the asymptotic approach by the default. In other words, these borrowers are interchangeable. Assuming that the portfolio is apportioned in K segments, which are defined here in terms of LTV and DSTI tranches, and defining S as a vector of standard normal systematic risk factors with realization s and correlation matrix R, losses can be rewritten as:

$$L(s) \approx \sum_{k=1}^{K} \sum_{j=1}^{J} \sum_{i=1}^{n_{kj}} u_i \, \Phi \left[\frac{\Phi^{-1}(\bar{p}_j) - w'_k s}{\sqrt{1 - w'_k R w_k}} \right] \qquad (3)$$

where w_k is the vector of sensitivities of the representative borrower of segment k to the systematic factors and n_{kj} is the number of exposures with rating j in segment k. Thus, the calibration of this model requires the estimation of J default thresholds, the K factor loadings w_k, and the correlation matrix R.

To calibrate the model, we use a generalized linear mixed regression model (GLMM) that combines fixed and random effects for observable and (latent) unobservable factors, respectively[22]. Indeed, Frey and McNeil (2003) have established a correspondence between the conditional default probability in Equation (3) and the specification of a GLMM. First, the default thresholds are the fixed effects. Second, the systematic risk factors correspond to the random effects. More specifically, the random effects variances correspond to the sensitivities w_b in Equation (3). Within this framework, the default probability in Equation (3) is defined as follows. Let Y_t be an (N × 1) vector of observed default data at time t and γ_t be the (K × 1) vector of random effects. The conditional expected default probability of obligor i at time t is then:

$$P(Y_{it} = 1|\gamma_t) = \Phi(x'_{ti}\beta + z_i\gamma_t) \qquad (4)$$

[22] The GLMM model is implemented, for instance, in Antonio and Berlant (2007), McNeil and Wendin (2007), or Dietsch and Petey (2015).

where $\Phi(\cdot)$ is the standard normal cdf [23], β denotes the vector of parameters associated with the fixed effect (the borrower's rating class), $x'_{ti} = [0, \dots, 1, \dots, 0]$ is a (1 × J) vector of dummies defining the rating of borrower *i* at time t and z_i is the design matrix of the random effects, here an identity matrix with size the number of random effects. The random effects are assumed to follow a multivariate normal distribution with 0 mean, covariance matrix Σ and correlation matrix *R*. Because we assume that borrowers within segments are interchangeable, the estimations of Σ and β do not involve individual borrowers but instead use the historical default rates within buckets built by crossing ratings with LTV or DSTI segments (tranches).

Once the credit risk parameters are estimated, the distribution of losses at the portfolio level is computed by a Monte Carlo simulation, with each simulated realization of the systematic risk factors being converted into a conditional default probability at the segment/rating level and, finally, into conditional expected losses at the portfolio level. Then, we compute the Value-at-Risk (VaR) as quantile of the simulated distribution of portfolio-wide losses. This VaR measures the economic capital requirements a lender would have to secure in order to cover potential losses at the chosen confidence level and time horizon. However, to assess the credit risk of a given group of borrowers within the portfolio, we need to compute its marginal contribution to economic capital. This requires to allocate the portfolio-wide economic capital to a given set of sub-portfolios. From the results of Tasche (1999) and Gouriéroux et al. (2000), the marginal contributions to the VaR can be expressed as the expected loss on a given exposure, conditional on losses reaching VaR:

$$RCVAR_i = E[L_i | L = VaR_\alpha(L)] = \frac{E\left[L_i \mathbf{1}_{VaR_\alpha(L)=L}\right]}{P[L = VaR_\alpha(L)]} \qquad (5)$$

Equation (5) suggests that if there is a positive probability for losses to reach a portfolio's VaR, then the computation of marginal contributions will rely heavily on the ability to estimate individual losses as aggregate losses approach VaR. Here, we follow the algorithm described in Tasche (2009) to compute marginal risk contributions at the rating/segment level. Finally, these marginal contributions can be aggregated at the sub-portfolio level to compare risk levels across segments of the portfolio having properly taken into account the dependence across segments at the portfolio level.

Results

[23] We focus on the probit link function because the normal distribution is the underlying link function that is assumed by the Basel 2 framework of credit risk (BCBS, 2006).

To compute economic capital requirements, we use a segmentation justified by the results of the previous section. It opposes the segment of borrowers without downside payment with three different subgroups of the remaining population of borrowers with positive downside payment, which vary according to the relative level of their DSTI ratio[24]. Indeed, the results gathered in Section 4 first highlight the specificity and homogeneity of these loans. They appear to be characterized by a higher average default probability. Moreover, their PD is widely independent from their DSTI. This invites to consider these loans as a specific segment of borrowers in terms of risk. However, Figure 4 also shows that, for loans with an initial down payment, the estimated default probability is an increasing function of DSTI. Therefore, in order to capture this increasing pattern, we subdivide the subpopulation of loans with down payment in three segments, using the regulatory threshold of 35% and a second, more arbitrary, threshold of 30%. Thus, the four segments are the following: (i) LTV ≥100%, (ii) LTV<100% & DSTI ≥ 35%, (iii) LTV<100% & 35% >DSTI≥30%, (iv) LTV<100% & DSTI < 30%.

To compute economic capital requirements, we consider two different sets of assumptions. First, we consider the Basel default (90 days past due) and 15% LGD flat rate. This corresponds to the common specification within the Internal Ratings Based (IRB) approach of Basel 2/3 capital requirements for credit risk. Second, we restrict the definition of default to closeout defaults and use the average empirical LGDs measured at the segment level. This second specification focuses on closeout defaults as they induce economic losses to the lenders, again neglecting the administrative costs occurred during the restructuration process. Moreover, banks are allowed under conditions, within the IRB approach, to use their own LDG estimates. Comparing the results from these two specifications could allow capturing the potential effects of either a specific exposure of closeout defaults to systematic risk as well as of a potential heterogeneity of LGD rates across DSTI and LTV level. In either case, we choose a 99.9% quantile of the probability distribution function, which is also the quantile in the Basel regulatory framework. In order to highlight possible changes over time in the risk of originated loans, all models distinguish the four vintages and use the history of the quarterly default rates[25].

[24] The choice to consider the entire subpopulation of borrowers without downside payment as a unique segment is justified by the fact that this subpopulation of borrowers is very homogeneous in terms of the borrowers' DSTI. However, this observation grounds on the computation of default probability, a measure of expected losses. It ignores potential difference within these loans in terms of exposure to systematic risk, which could lead to differences in terms of economic capital. In order to address this issue, we apply the same methodology restraining the analysis to loans without down payment, considering three segments (DSTI < 30%, 30% <= DSTI < 35%, and 35% < DSTI). The credit risk parameters and the resulting economic capital ratios are very close across the three classes, which justifies their aggregation.

[25] Tables A.5 in Appendix A presents the value of the risk parameters provided by the estimation of the GLMM model.

Table 8 presents the results for the specification with Basel default and the flat 15% LGD. These results first confirm the observations made when considering default at the loan level. Table 8 shows that the relative amount of EC distinguish very clearly the segment of loans without downside payment from the others. Consistent with the previous results, this confirms the overall higher credit risk of these loans. This effect is even more marked when we consider loans issued either just before or during the GFC and the Eurozone debt crisis. While all loans issued during that period appear to be riskier than those issued before and after, the increase is more striking for no down payment loans. Considering the loans issued with a positive down payment, we observe a weak decreasing pattern for all vintages. Again, this is overly consistent with the previous results (see Figure 4) showing that the positive association between DSTI and PD is concave.

Table 8 Economic capital and segment contributions using Basel default and a flat 15% LGD rate

	2000-2004	2005-2008Q2	2008Q3-2012	2013-2016
Panel A Economic capital ratios (EC/Exposures), in %				
LTV ≥100%	0.039	0.093	0.101	0.034
LTV<100% & DSTI ≥ 35%	0.025	0.043	0.038	0.017
LTV<100% & 35% >DSTI≥30%	0.027	0.028	0.039	0.014
LTV<100% & DSTI < 30%	0.018	0.028	0.032	0.015
Panel B Contributions to total risk (in% of total EC)				
LTV ≥100%	31.2	49.7	49.4	43.2
LTV<100% & DSTI ≥ 35%	10.7	13.0	13.4	15.5
LTV<100% & 35% >DSTI≥30%	18.4	10.3	13.8	11.9
LTV<100% & DSTI < 30%	39.8	27.0	23.5	29.4

Moreover, considering different vintages of loan issuance highlights the effect of the business cycle on bank lending policies. As observed in the US (Mian and Sufi, 2009), banks originated riskier loans as house prices rose until the outbreak of the GFC. This is consistent with the observed simultaneous growth of house prices and lending standards (see Figure 1, Section 3). Then, lending standards somehow remained overly stable at these high levels. Nevertheless, the loans issued during this period bear credit risk levels overly similar to these issued just before the GFC. Finally, the EC ratios for the last vintage seem to reflect a return to the situation prevailing in the beginning of the 2000s. However, although we follow loans at least three years after their issuance, we cannot completely exclude a censure effect that likely affects the number of defaults and losses during this period could impede this result. However, the overall risk pattern across the four segments of our segmentation remains robust over the business cycle, reflecting structural features of the French market for housing loans. Moreover, we observe that the segment of operations without downside payment contributes the most to the EC whatever the vintage period, particularly for the two intermediate vintage periods. Indeed, Panel B from Table 8 shows that loans without down payment represent up to 50% of total EC although they represent about 20-25% of loan production over the entire period. Hence, credit risk appears to be concentrated on no down payment loans.

Our second credit risk specification that concentrates on closeout defaults and uses empirical LGDs even strengthens these first results. From Table 6 (Panel A), we first observe that EC levels are lower. Indeed, while empirical LGDs are larger than the 15% default flat rate, the default rates used in this second specification are lower, as we consider a narrower definition of default. Moreover, the variances and correlation of random effects are rather close (see Table A.4 in the Appendix). However, the concentration of credit risk on loans without an initial downside payment is even more pronounced as these consumed up to 60% of the total EC in the years preceding the GFC. More precisely, the shares of EC of no down payment loans are similar across our two specifications for the 2000-2004 and 2013-2016 vintages, while they are larger for the vintages immediately preceding and covering the GFC. This confirms the larger exposure of these loans to the business cycle, reflecting changes in the lending policies of commercial banks. Finally, Table 9 confirms the slightly decreasing pattern between credit risk and DSTI for loans with an initial downside payment.

Table 9 Economic capital and segment contributions using closeout default and empirical LGDs

	2000-2004	2005-2008Q2	2008Q3-2012	2013-2016
Panel A Economic capital ratios (EC/Exposures), in %				
LTV ≥100%	0.020	0.083	0.095	0.028
LTV<100% & DSTI ≥ 35%	0.012	0.019	0.032	0.013
LTV<100% & 35% > DSTI≥30%	0.013	0.018	0.028	0.016
LTV<100% & DSTI < 30%	0.009	0.016	0.020	0.015
Panel B Contributions to total risk (in% of total EC)				
LTV ≥100%	32.2	60.9	54.4	39.3
LTV<100% & DSTI ≥ 35%	10.7	7.8	13.5	13.1
LTV<100% & 35% > DSTI≥30%	18.1	9.4	12.0	15.0
LTV<100% & DSTI < 30%	39.1	21.7	18.1	32.6

7. Conclusions and implications

Analyzing the association between credit risk and DSTI or LTV ratios in the French housing loans market outside any regulatory framework, we obtain the following results. First, both lending standards are positively associated to default risk at the loan level. Moreover, these patterns are only marginally non-monotonic. Therefore, as widely observed in the literature, these ratios indeed provide potentially relevant tools for the design of macroprudential policies. However, as also observed in some research, the association with default risk is tighter for LTV than for DSTI, making the former the preferred tool in most countries, especially in the perspective of a bank resilience channel of macroprudential policy. Moreover, we highlight the specificity of loans without down payment in the French context. Representing about 20%-25% of all housing loans for the acquisition of the main residence, they have larger default probabilities.

Our analysis of the interdependence of the two ratios show that adjustments of loans characteristics (value of acquired house, loan maturity, in particular) allow, for a fraction of borrowers, the decrease (or stability) of DSTI, while borrowers' down payments decrease. In fact, results show that this effect is concentrated on no/low down payment borrowers. Thus, the DSTI ratio does not allow on its own the proper identification of the riskiest borrowers. Moreover, adopting the lenders' perspective and accordingly considering risk at the portfolio level shows that no down payment loans expose lenders to a potential concentration risk, as they bear a disproportionate share of lenders potential losses, widely escaping the recent regulatory framework. These results are quite robust across the business cycle. Changes in lending standards contributed to the accumulation of risk ahead and during the GFC.

Overall, these results could cast doubt on the ability of a macroprudential policy solely based on DSTI to characterize consistently the risk of housing loans and efficiently apprehend bank risk resiliency. Thus, the potential borrowers impacted by the prudential DSTI limit may not be (only) the riskier. However, the DSTI ratio may not intrinsically be inferior to the LTV ratio as a risk indicator, but it may be "managed" by lenders, using the loan amount and the loan maturity as instruments. This result advocates for the complementary maturity limit.

Main lesson of this paper is perhaps that credit risk has to be considered at the global (lenders' portfolio) level. Adopting this perspective puts the emphasis on the control of concentration risk. Therefore, the sustainability of any exception in the fixation of limits, such as for instance in favor of the first homebuyers that are frequently characterized by with a low level of down payment, should be evaluated not only in its impact of the concerned borrowers' probability to default but also in terms of its impact on the concentration risk.

References

ACPR-Banque de France. (2017). “Le financement de l’habitat en 2016.” Analyses et Synthèses, 82, July. https://acpr.banque-france.fr/le-financement-de-lhabitat-en-2016.

Akerlof, G. A., O. Blanchard, D. Romer, and J. Stiglitz, 2014, What Have We Learned? Macroeconomic Policy after the Crisis (MIT Press, Cambridge, MA).

Ampudia, M. M. Lo Duca, M. Farkas, G. Pérez-Quirós, M. Pirovano, G. Rünstler, E. Tereanu, 2021, On the effectiveness of macroprudential policy, ECB Working Paper Series N°2559.

Antonio, Katrien, Jan Berlant. (2007). “Actuarial statistics with generalized linear mixed models.” Insurance: Mathematics and Economics 40. 58-76.

de Araujo Douglas, Joao Barroso, Rodrigo Gonzalez, 2020, Loan-to-value policy and housing finance: Effects on constrained borrowers, Journal of Financial Intermediation, 20.

Areki, Rabah, Thorsten Beck, Robert DeYoung, John Duca, Prakash Louganil, and Anthony Murphy. (2015). “Conference on Housing, Stability, and the Macroeconomy: International Perspectives.” Journal of Money, Credit and Banking 47. 1-11.

Armstrong Jed, Hayden Skilling, Fang Yao, 2019, Loan-to-value ratio restrictions and house prices: Micro evidence from New Zealand, Journal of Housing Economics, 44, 88-98.

Avery, Robert, Raphael Bostic, Paul Calem, and Glenn Canner. (1996). “Credit risk, credit scoring, and the performance of home mortgages.” Federal Reserve Bulletin. July. 621-648.

Barbalia L., S. Manzan & E. Tosetti, 2021. Forecasting loan default in Europe with machine learning. Journal of Financial Econometrics, https://doi.org/10.1093/jjfinec/nbab010.

Bajari, Patrick, Sean Chu, and Minjung Park. (2008). “An empirical model of subprime mortgage default from 2000 to 2007.” NBER Working Paper 14625.

BCBS. (2006). “Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework - Comprehensive Version”. Basel Committee on Banking Supervision.

Campbell, John, Joao Cocco. (2015). “A model of mortgage default.” Journal of Finance 70(4). 1495–1554.

Campbell, J. Y. N. Clara, J. F. Cocco, 2020, Structuring mortgages for macroeconomic stability, NBER Working Paper n°27676.

Cerutti Eugenio, Stijn Claessens, and Luc Laeven. (2017). “The use and effectiveness of macropudential policies: New evidence.” Journal of Financial Stability 28. 203-224.

Chan, Sewin, Michael Gedal, Vicki Been, and Andrew Haughwout. (2013). “The role of neighbourhood characteristics in mortgage default risk: Evidence from New York City.” Journal of Housing Economics 22. 100-118.

Chen, Hui, M. Michaux, and N. Roussanov, 2020, Houses as ATMs: mortgage refinancing and macroeconomic uncertainty, The Journal of Finance 75, 323 - 375.

Claessens, Stijn, Swati Ghosh, Roxana Mihet. (2013). "Macro-prudential policies to mitigate financial system vulnerabilities." Journal of International Money and Finance 39. 153-185.

Christophides L.N., T. Stengos & R. Swidinsky, 1997. On the calculation of marginal effects in the bivariate probit model, Economics Letters 54, 203-208.

CGFS Committee on Global Financial Stability. (2012). "Operationalising the selection and application of macroprudential instruments." CGFS Papers 48.

CGFS Committee on Global Financial Stability. (2016). "Experiences with the ex ante appraisal of macroprudential instruments." CGFS Papers 56.

Guiso, Luis, P. Sapienza and L. Zingales, (2013). The Determinants of Attitudes towards Strategic Default on Mortgages. The Journal of Finance, 68, 1473-1515.

Corradin, Stefano. (2014). Household leverage. Journal of Money, Credit and Banking 46(4). 567-613.

Corbae, Dean, and Erwan Quintin, 2015, Leverage and the foreclosure crisis, Journal of Political Economy, 123, 1 - 65.

Couailler C., J. Idier, R. Jimborean, 2018, L'apport personnel obligatoire : un outil macroprudentiel de plus en plus utilisé pour prévenir le risque immobilier Bulletin BDF n°215.

Crowe, Christopher, Giovanni Dell'Ariccia, Deniz Igan, and Pau Rabanal. (2013). How to deal with real estate booms: Lessons from country experiences. Journal of Financial Stability 9(3). 300-319.

Darbar, Salim, Xiaoyong Wu. (2015). "Experiences with macroprudential policy – Five case studies." IMF working paper 15/123.

Dell'Ariccia, Giovanni, Deniz Igan, and Luc Laeven. (2012). "Credit booms and lending standards: Evidence from the subprime mortgage market." Journal of Money, Credit and Banking 44. 367–384.

Diaz-Serrano, Luis. (2005). "Income volatility and residential mortgage delinquency across the EU." Journal of Housing Economics 14. 153-177.

Dietsch, Michel, Joël Petey. (2015). "The credit-risk implications of housing ownership promotion: The effects of public subsidies and adjustable-rate loans." Journal of Housing Economics 28. 103-120.

Ding, Lei, Roberto Quercia, Wei Li, and Janneke Ratcliffe. (2011). "Risky borrowers or risky mortgages: disaggregating effects using propensity score models." Journal of Real Estate Research 33(2). 245–278.

Duca, John, Janine Aron, John Muellbauer, Keiko Murata, and Anthony Murphy. (2012). "Credit, Housing Collateral and Consumption: Evidence from Japan, the UK and the U.S." The Review of Income and Wealth 58(3). 397-423.

Duca, John, John Muellbauer, and Anthony Murphy. (2011). "House Prices and Credit Constraints: Making Sense of the U.S. Experience." The Economic Journal 121. 533-551.

European Systemic Risk Board (ESRB). (2016). A Review of Macroprudential Policy in the EU in 2015, May.

European Systemic Risk Board (ESRB), National measures of macroprudential interest in the EU/EEA, European Systemic Risk Board (https://www.esrb.europa.eu/national_policy/other/html/index.en.html, accessed June 2021).

Filippini M., W.H. Green, N. Kumar & A. Martinez-Cruz, 2018. A note on the different interpretation of the correlation parameters in the Bivariate Probit and the Recursive Bivariate Probit, Economics Letters 167, 104-107.

Foote, Christopher, Kristopher Gerardi, and Lorenz Paul. (2009). "Reducing foreclosures." NBER Macroeconomics Annual 24. 89–138.

Gadea, M. D. and Perez Quiros, G., 2021. "Financial stability and income distribution" mimeo, European Central Bank

Galán J.E. and Matías Lamas, 2019. Beyond the LTV ratio: New macroprudential lessons from Spain, Banco de Espana, Documentos de Trabajo. N°1931.

Gambacorta Leonardo, Andrés Murcia, 2020. The impact of macroprudential policies in Latin America: An empirical analysis using credit registry data, Journal of Financial Intermediation.

Gaudêncio J., A. Mazany, C. Schwarz, 2019/ The impact of lending standards on default rates of residential real estate loans ECB Occasional paper n°220.

Gordy, Michael. (2003). "A risk-factor model foundation for ratings-based bank capital rules." Journal of Financial Intermediation, 12(3). 199-232.

Gouriéroux, Christian, Jean-Paul Laurent, Olivier Scaillet. (2000). "Sensitivity analysis of Values at Risk." Journal of Empirical Finance, 7. 225-245.

Greene W.H., 1996. Marginal effects in the bivariate probit model, WP EC-96-11, New York University.

Gross, M. and F. Poblacion, 2016, Assessing the efficacy of borrower-based macroprudential policy using an integrated micro-macro model for European households, ECB Working Paper 1881, February.

Hartmann, Philip. (2015). "Real Estate Markets and macroprudential Policy in Europe." Journal of Money, Credit and Banking, 47. 69–80.

Hatchondo, Juan, Leonardo Martinez, and Juan Sánchez. (2015). "Mortgage defaults." Journal of Monetary Economics 76. 173-190.

Haughwout, Andrew, Richard Peach, and Joseph Tracy. (2008). "Juvenile Delinquent Mortgages: Bad Credit or Bad Economy?" Journal of Urban Economics 64(2). 246-57.

Haurin, Donald. (1991). "Income variability, homeownership, and housing demand." Journal of Housing Economics 1. 60-74.

He, Dong, Erlend Nier and Heedon Kang, 2016, Macroprudential measures for addressing housing sector risks, BIS working paper n°86, Macroprudential policy, September.

Igan, Deniz, Heedon Kang. (2011). "Do Loan-to-Value and Debt-Service-To-Income Limits Work? Evidence from Korea." IMF working paper 11/297.

IMF, (2013), Key aspects of macroprudential policies.

Jiménez, Gabriel, Javier Mencía, 2009, Modelling the distribution of credit losses with observable and latent factor, Journal of Empirical Finance, vol. 16, 235–253.

Johnson, Kathleen, Geng Li. (2010). "The debt-payment-to-income ratio as an indicator of borrowing constraints: Evidence from two household surveys." Journal of Money, Credit and Banking 42(7). 1373-1390.

de Jong, Jasper, de Veirman, Emmanuel, 2019, Heterogeneity and Asymmetric Macroeconomic, Netherlands Central Bank, Research Department, DNB Working Papers.

Kelly, Robert, Fergus. McCann and Conor. O'Toole, 2018, Credit conditions, macroprudential policy and house prices. Journal of Housing Economics, vol. 41, 153-167.

Kelly Robert, Conor O'Toole, 2018, Mortgage default, lending conditions and macroprudential policy: Loan-level evidence from UK buy-to-lets, Journal of Financial Stability, Volume 36, Pages 322-335.

Kuttner, Kenneth, Ilhyock Shim. (2016). "Can non-interest rate policies stabilise housing markets? Evidence from a panel of 57 economies." Journal of Financial Stability 26(C). 31-44.

Lang J.H., M. Pirovano, M. Rusnàk & C. Schwarz, 2020. Trends in residential real estate lending standards and implications for financial stability, Financial Stability Review, May, European Central Bank.

Laufer, Steven. (2018). "Equity extraction and mortgage default." Review of Economic Dynamics 28, 1-33.

Liang, Kung-Yee and Scott L. Zeger. 1986. Longitudinal Data Analysis Using Generalized Linear Models. *Biometrika*, 73(1),13-22.

Lim, C., F. Columbia, A. Costa, P. Konsamut, A. Otani, M. Saiyid, T. Wezel and X. Wu (2011). Macroprudential Policy: What Instruments and How to Use Them? Lessons from Country Experiences. IMF Working Paper No. 238.

Lucas, Andre, Peter Klaassen, Pieter Spreij, and Stefan Straetmans. (2001). "An analytic approach to credit risk of large corporate bond and loan portfolios." Journal of Banking and Finance 25. 1635-1664.

Mayer, Christopher, Karen Pence, and Shane Sherlund. (2009). "The Rise in Mortgage Defaults." Journal of Economic Perspectives 23(1). 27-50.

McDonald, Chris. (2015). "When is macroprudential policy effective?" BIS working paper 496.

McNeil, Alexander, Jonathan Wendin. (2007). "Bayesian inference for generalized linear mixed models of portfolio credit risk." Journal of Empirical Finance 14. 131-149.

Mian, Atif, Amir Sufi. (2009). "The consequences of mortgage credit expansion: Evidence from the 2007 mortgage default crisis." Quarterly Journal of Economics 124(4). 1449–1496.

Mian, Atif, Amir Sufi. (2011). "House prices, home equity based borrowing, and the U.S. household leverage crisis." American Economic Review 101. 2132–2156.

Morgan Peter J., Paulo José Regis, Nimesh Salike, 2019. LTV policy as a macroprudential tool and its effects on residential mortgage loans, Journal of Financial Intermediation, Volume 37, 2019, 89-103.

Nier E., R. Popa, M. Shamloo, L. Voinea, 2019, Debt Service and Default: Calibrating Macroprudential Policy Using Micro Data, IMF working paper N°182.

Okah, Ebiere, James Orr. (2010). "Subprime Mortgage Lending in New York City: Prevalence and Performance." Federal Reserve Bank of New York Staff Report 432.

Punzi Maria Teresa, Katrin Rabitsch, 2018, Effectiveness of macroprudential policies under borrower heterogeneity, Journal of International Money and Finance, Volume 85, 251-261,

Quercia, Roberto, Anthony Pennington-Cross, and Chao Yue Tian. (2012). "Mortgage default and prepayment risks among moderate- and low income households." Real Estate Economics 40. S159–S198.

Qi, M., and X. Yang, 2009, Loss given default of high loan-to-value residential mortgages. Journal of Banking and Finance, vol.33, 788-799.

Richter, Bjorn, Schularick, Moritz, Shim, Ilhyock, 2019, The Costs of Macroprudential Policy, Journal of International Economics, May 2019, v. 118, 263-82.

Sherlund, Shane. (2008). "The past, present and future of subprime mortgages." Federal Reserve Board Finance and Economics Discussion Series 2008-63.

Tasche, Dirk. (1999). "Risk contributions and performance measurement." working paper Technische Universität München.

Tasche, Dirk. (2009). "Capital allocation for credit portfolios with kernel estimators." Quantitative Finance 9(5). 581-595.

Appendix

Appendix A Marginal effects and odds ratios for the BP and the RBP models.

The computation of marginal effects for continuous regressors and odds ratios for binary and multinomial discrete variables for the BP and RBP models involve the following 4 probabilities, where Φ_2 denotes the bivariate normal cdf (see Green, 1996 and Christophides et al., 1997)[26]:

$$Prob[DSTI = 1, LTV = 1] = \Phi_2(\gamma' x, \delta' x + \alpha, \rho)$$

$$Prob[DSTI = 1, LTV = 0] = \Phi_2(-\gamma' x, \delta' x, -\rho)$$

$$Prob[DSTI = 0, LTV = 1] = \Phi_2(\gamma' x, -\delta' x - \alpha, -\rho)$$

$$Prob[DSTI = 0, LTV = 0] = \Phi_2(-\gamma' x, -\delta' x, -\rho)$$

Besides the marginal effects of LTV on DSTI within the RBP model (see Section 5 in the main text), we compute odds ratios and marginal effects of explanatory variables on, respectively, the non-conditional expectations of DSTI and LTV. Hence, we consider the two following expectations:

$$E[DSTI|x] = Prob[LTV = 1]E[DSTI|LTV = 1, x] + Prob[LTV = 0]E[DSTI|LTV = 0, x]$$
$$= \Phi_2(\gamma' x, \delta' x + \alpha, \rho) + \Phi_2(-\gamma' x, \delta' x, -\rho)$$

$$E[LTV|x] = Prob[DSTI = 1]E[LTV|DSTI = 1, x] + Prob[DSTI = 0]E[LTV|DSTI = 0, x]$$
$$= \Phi_2(\gamma' x, \delta' x + \alpha, \rho) + \Phi_2(\gamma' x, -\delta' x - \alpha, -\rho)$$

Given the preceding definitions, the two following ratios define the odds ratios for a given discrete variable x_j taking value Y relative to a reference level REF, where x^- denotes explanatory variables excluding x_j:

$$\frac{E\left[DSTI\middle|x_j = Y\right]}{E\left[DSTI\middle|x_j = REF\right]} = \frac{\Phi_2\left(\gamma' x^- + \gamma_{jY}, \delta' x^- + \delta_{jY} + \alpha, \rho\right) + \Phi_2\left(-\gamma' x^- - \gamma_{jY}, \delta' x^- + \delta_{jY}, -\rho\right)}{\Phi_2(\gamma' x^-, \delta' x^- + \alpha, \rho) + \Phi_2(-\gamma' x^-, \delta' x^-, -\rho)}$$

$$\frac{E\left[LTV\middle|x_j = Y\right]}{E\left[LTV\middle|x_j = REF\right]} = \frac{\Phi_2\left(\gamma' x^- + \gamma_{jY}, \delta' x^- + \delta_{jY} + \alpha, \rho\right) + \Phi_2\left(\gamma' x^- + \gamma_{jY}, -\delta' x^- - \delta_{jY} - \alpha, -\rho\right)}{\Phi_2(\gamma' x^-, \delta' x^- + \alpha, \rho) + \Phi_2(\gamma' x^-, -\delta' x^- - \alpha, -\rho)}$$

Finally, we define the marginal effects for a continuous variable x_j:

$$\frac{\partial E[DSTI|x]}{\partial x_j} = \phi(\gamma' x)\Phi\left[\frac{\delta' x + \alpha - \rho\gamma' x}{\sqrt{1-\rho^2}}\right]\gamma_j + \phi(\delta' x + \alpha)\Phi\left[\frac{\gamma' x - \rho(\delta' x + \alpha)}{\sqrt{1-\rho^2}}\right]\delta_j$$
$$- \phi(-\gamma' x)\Phi\left[\frac{\delta' x - \rho\gamma' x}{\sqrt{1-\rho^2}}\right]\gamma_j + \phi(\delta' x)\Phi\left[\frac{-\gamma' x + \rho\delta' x}{\sqrt{1-\rho^2}}\right]\delta_j$$

$$\frac{\partial E[LTV|x]}{\partial x_i} = \phi(\gamma' x)\Phi\left[\frac{\delta' x + \alpha - \rho\gamma' x}{\sqrt{1-\rho^2}}\right]\gamma_j + \phi(\delta' x + \alpha)\Phi\left[\frac{\gamma' x - \rho(\delta' x + \alpha)}{\sqrt{1-\rho^2}}\right]\delta_j$$
$$+ \phi(\gamma' x)\Phi\left[\frac{-\delta' x - \alpha + \rho\gamma' x}{\sqrt{1-\rho^2}}\right]\gamma_j - \phi(-\delta' x - \alpha)\Phi\left[\frac{\gamma' x + \rho(\delta' x + \alpha)}{\sqrt{1-\rho^2}}\right]\delta_j$$

[26] For the sake of notational simplicity, we drop the i subscript of the $DSTI_i$ and LTV_i binary variables. Here, we detail computations for the RBP model. However, results for the BP model are obtained just by setting $\alpha = 0$.

Table A.1 Definitions of variables

Debt-service-to-income (DSTI)	Ratio of all debt repayments (including previous debt) over income
Loan-to-Value (LTV)	Ratio of the borrowed amount to the home value
Age	Age of the borrower in years if single, arithmetic mean if borrowers are a couple. In the computation of average marginal effects, we consider a 1 years change in Age.
Income	Annual income of the borrowing household, in euros. In the computation of average marginal effects, we consider a 1k euros change.
Financial assets	Gross financial assets as a percentage of the borrowed amount. In the computation of average marginal effects, we consider change of 10 percentage points.
Home value	Acquisition price of the acquired real estate, without taxes and fees. In the computation of average marginal effects, we consider a 1k euros change.
Length	Length of the borrower-lending bank relationship at time of origination (in days).
Maturity	Initial maturity of the loan at origination in months. When there are several loans, maturity if the highest maturity of these loans. In the computation of average marginal effects, we consider a 1 month change.
Previous debt	Level of debt (in euros) preexisting the origination of the housing loan(s). In the computation of average marginal effects, we consider a 1k euros years change.
Prev. Home owner	Equal to 1 if the borrowing household has real estate assets before the origination, 0 else.
Occupation	Occupation of the borrower if single, occupation of the main borrower if a couple, 17 modalities
Civil status	Civil status of the borrowing households, 8 modalities
Children	Number of children of the borrower, winsorized to 4
Parisian region	Equal to 1 if the acquired housing is located in the Parisian region (Île de France), 0 else.
Default	Basel default: Equal to 1 if 90 days past due, 0 else Closeout default: Equal to 1 if a Basel default leads to a closeout, 0 else.

Table A.2 Descriptive statistics

	DSTI			LTV					
	DSTI<35%	DSTI≥35%	Diff	LTV<100%	LTV≥100%	Diff	Default	Alive	Diff
Age	39.34	38.54	-0.80***	39.12	39.98	0.86***	37.50	39.20	-1.70***
Income	57054	59071	2017***	58,078	62,884	4,806***	49,018	57,495	-8,476***
Financial assets (%)	25.17	22.83	-2.34***	27.60	18.70	-8.90***	11.02	24.85	-13.83***
Home value	189,675	221,554	31,879***	195,726	198,080	2,354***	177,548	196,163	-18,614***
Length	5,790	5,918	128***	5,817	5,943	126***	4,779	5,825	1,046***
Maturity	176.1	207	30.9***	182	215	33***	231	181	49***
Previous debt	3,691	10,979	7,287***	4,925	7,903	2,978***	3,234	5,046	-1,812***
Prev. Home owner	41.28	62.15	***	46.43	63.94	***	28.13	45.26	***
Occupation			***			**			***
Managers, public sector	9.72	8.69		9.39	7.88		9.57	4.75	
Employees, public sector	9.80	9.51		9.32	12.38		9.75	9.09	
Unemployed	0.17	0.15		0.17	0.21		0.17	0.21	
Students	0.15	0.12		0.16	0.08		0.15	0.08	
Retired	4.63	3.02		4.20	3.58		4.35	2.41	
Without activity	0.97	0.96		0.97	0.89		0.96	1.07	
Artisans and shopkeepers	2.31	3.00		2.53	2.17		2.42	4.55	
Farmers	0.21	0.23		0.22	0.20		0.21	0.20	
Executives	2.14	2.83		2.32	2.41		2.26	3.03	
Professionals	1.99	2.38		2.07	2.08		2.05	2.96	
Professionals (health)	2.86	3.63		3.10	3.22		3.01	2.11	
Other professionals	0.82	0.69		0.89	0.49		0.80	1.05	
Workers	8.40	7.43		8.62	7.14		8.22	8.42	
Managers, private sector	31.84	34.01		32.68	29.81		32.31	23.70	
Employees, private sector	23.02	22.52		22.35	26.56		22.83	35.24	
Temporary workers	0.96	0.83		1.01	0.89		0.94	1.15	
Civil status			***			***			***
Married couple	51.07	45.58		49.23	52.99		40.36	50.14	
Single woman divorced	3.69	3.36		3.66	3.04		3.86	3.63	
Single woman	9.38	10.46		9.70	6.97		9.05	9.58	
Single man divorced	2.74	5.12		3.25	2.93		5.24	3.16	
Single man	12.37	17.89		13.58	11.94		19.01	13.34	
Couple	12.22	10.42		12.00	13.82		12.95	11.88	
Couple w/ divorced partner	2.10	2.20		2.20	2.10		3.44	2.10	
Other	6.83	4.97		6.37	6.21		6.09	6.16	
Children			***			***			***
0	68.16	64.28		66.31	57.56		59.85	67.51	
1	10.97	12.32		11.66	14.45		14.35	11.19	
2	13.09	14.50		13.74	17.90		14.28	13.34	
3	4.17	4.88		4.39	5.96		5.95	4.29	
4 +	3.61	4.01		3.90	4.13		5.57	3.66	
Parisian region	33.37	32.61	***	33.05	32.04	***	32.91	33.23	

Table A.2 gathers the mean values and distributions of the control variables and the p-values of equal means/distributions. For continuous variables, we evaluate the difference in means with a t-test. For categorical variables, we compute the χ^2 statistic for equal distributions. ***,**,* denote p-values of the parameter estimates at the 1%, 5%, 10% level, respectively.

Table A.3: Relative values of house value and loan maturity by LTV and DSTI tranches by vintages

vintage		DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35	DSTI<25	25<=DSTI<30	30<=DSTI<35	DSTI=>35
		house price relative to first DSTI tranche				loan maturity relative to first DSTI tranche			
2000-2004	LTV<=80	100	97	99	106	100	109	112	114
	80<LTV<=90	100	100	105	117	100	108	109	109
	90<LTV<100	100	99	106	127	100	108	108	106
	LTV=>100	100	100	110	141	100	107	107	106
2005-2008Q2	LTV<=80	100	97	97	101	100	113	117	120
	80<LTV<=90	100	97	101	107	100	111	114	114
	90<LTV<100	100	96	102	111	100	112	114	112
	LTV=>100	100	100	106	124	100	111	113	112
2008Q3-2012	LTV<=80	100	97	98	107	100	113	117	118
	80<LTV<=90	100	100	104	114	100	110	111	110
	90<LTV<100	100	100	106	118	100	110	110	108
	LTV=>100	100	106	112	131	100	110	110	107
2013-2016	LTV<=80	100	100	103	116	100	110	112	114
	80<LTV<=90	100	106	111	128	100	105	105	106
	90<LTV<100	100	107	114	132	100	104	105	106
	LTV=>100	100	108	115	143	100	106	106	104
		house price relative to first LTV tranche				loan maturity relative to first LTV tranche			
2000-2004	LTV<=80	100	100	100	100	100	100	100	100
	80<LTV<=90	78	80	83	86	120	119	117	115
	90<LTV<100	73	74	78	87	123	122	119	114
	LTV=>100	63	65	70	83	119	117	114	110
2005-2008Q2	LTV<=80	100	100	100	100	100	100	100	100
	80<LTV<=90	82	83	85	86	120	119	117	113
	90<LTV<100	77	77	81	84	124	123	121	115
	LTV=>100	69	71	75	84	120	119	117	111
2008Q3-2012	LTV<=80	100	100	100	100	100	100	100	100
	80<LTV<=90	77	80	82	83	125	122	120	117
	90<LTV<100	68	71	74	75	132	128	125	121
	LTV=>100	58	63	66	71	130	126	123	118
2013-2016	LTV<=80	100	100	100	100	100	100	100	100
	80<LTV<=90	78	83	84	86	127	120	119	118
	90<LTV<100	68	72	74	78	134	127	125	124
	LTV=>100	57	61	63	71	130	125	122	119

Table A.4, Default model, significance tests

Age	1309.67***
Income	295.21***
Financial assets (%)	982.98***
Home value	2091.71***
Length	2170.65***
Maturity	3403.43***
Previous debt	82.14***
Prev. Home owner	127.24***
Occupation	1763.91***
Civil status	1023.84***
Children	998.74***
Parisian region	51.29***

Table A.2 shows F statistics for the significance of partial effects associated to the logistic regressions defined by Equations (1) and (2) (Panel A) and the default model defined by Equation (3) (Panel B). ***,**,* denote p-values of the parameter estimates at the 1%, 5%, 10% level, respectively.

Table A.5 Credit parameter estimates

Tables A.4.1.1 to A.4.2.4 show the parameter estimates of the GLMM probit binomial model underlying the computation of economic capital. For each table, Panel A shows the estimated default thresholds at the LTV-DSTI bucket/rating level. All default thresholds have p-values lower than 1%. We perform F tests on the following set of constraints to test the homogeneity of default thresholds across LTV-DSTI buckets, where *k* denotes a LTV-DSTI bucket and *r* denotes a rating level:

$$\Phi^{-1}(\bar{p}_r^1) = \cdots = \Phi^{-1}(\bar{p}_r^k) = \cdots = \Phi^{-1}(\bar{p}_r^K), r = 1 \dots R$$

Panel B shows the random effects variances at the industry level and Panel C their correlations. ***,**,*: significant at the 1%, 5%, 10% level, respectively.

Table A.5.1.1 Basel default and 15% LGD, 2000-2004

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	21.46***	-3.6001	-3.5536	-3.5717	-3.6951
2	12.42***	-3.3357	-3.3194	-3.2821	-3.3630
3	2.69**	-2.9627	-3.0177	-2.9903	-2.9869
		Panel B Random effects variances			
		0.01893***	0.01664***	0.01711***	0.01715***
		Panel C Random effects correlations			
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	0.92	1		
	35% >DSTI≥30%	0.98	1	1	
	DSTI < 30%	0.97	1	0.98	1

Table A.5.1.2 Basel default and 15% LGD, 2005-2008Q2

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	13.07***	-3.5260	-3.6248	-3.6611	-3.6834
2	17.54***	-3.2731	-3.3474	-3.3267	-3.3585
3	57.39***	-2.8921	-3.0287	-2.9607	-3.0020
		Panel B Random effects variances			
		0.03674***	0.03335***	0.01723***	0.02738***
		Panel C Random effects correlations			
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	0.99	1		
	35% >DSTI≥30%	0.99	1	1	
	DSTI < 30%	1	0.99	0.99	1

Table A.5.1.3 Basel default and 15% LGD, 2008Q3-2012

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	11.56***	-3.5743	-3.6481	-3.6369	-3.7134
2	55.22***	-3.1993	-3.2846	-3.3055	-3.3466
3	55.14***	-2.8332	-2.9440	-2.9183	-2.9382
		Panel B Random effects variances			
		0.03228***	0.02419***	0.02557***	0.02866***
Panel C Random effects correlations					
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	1	1		
	35% >DSTI≥30%	1	1	1	
	DSTI < 30%	0.99	0.99	1	1

Table A.5.1.4 Basel default and 15% LGD, 2012-2016

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	3.15**				
2	9.08***				
3	2.40*				
		Panel B Random effects variances			
		0.01136***	0.01245***	0.004832**	0.01336***
Panel C Random effects correlations					
	Paramètres de crédit	1			
LTV < 100%	DSTI ≥ 35%	0.93	1		
	35% >DSTI≥30%	0.96	1	1	
	DSTI < 30%	1	0.85	1	1

Table A.5.2.1 Closeout default and empirical LGD, 2000-2004

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	11.78***	-3.8593	-3.8203	-3.7931	-3.9446
2	3.59**	-3.5771	-3.5641	-3.5549	-3.6085
3	6.71***	-3.2206	-3.2972	-3.2779	-3.3016
		Panel B Random effects variances			
		0.01407***	0.01831***	0.02253***	0.01755***
Panel C Random effects correlations					
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	0.98	1		
	35% >DSTI≥30%	0.86	0.98	1	
	DSTI < 30%	0.98	1	1	1

Table A.5.2.2 Closeout default and empirical LGD, 2005-2008Q2

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	8.27***	-3.7986	-3.8675	-3.9295	-3.9763
2	10.84***	-3.5369	-3.6109	-3.5687	-3.6317
3	33.90***	-3.1736	-3.3189	-3.2198	-3.3067
		Panel B Random effects variances			
		0.03751***	0.02522***	0.02132***	0.02699***
		Panel C Random effects correlations			
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	1	1		
	35% >DSTI≥30%	0.94	1	1	
	DSTI < 30%	1	1	0.98	1

Table A.5.2.3 Closeout default and empirical LGD, 2008Q3-2012

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	12.67***	-3.8160	-3.9829	-3.9614	-4.0637
2	24.31***	-3.5159	-3.5973	-3.6059	-3.6782
3	25.44***	-3.1511	-3.2879	-3.2198	-3.2488
		Panel B Random effects variances			
		0.03889***	0.03886***	0.03328***	0.02984***
		Panel C Random effects correlations			
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	0.97	1		
	35% >DSTI≥30%	1	0.94	1	
	DSTI < 30%	0.99	0.97	0.99	1

Table A.5.2.4 Closeout default and empirical LGD, 2012-2016

Panel A Default thresholds					
Rating	Homogeneity test	LTV ≥100%	LTV<100%		
			DSTI ≥ 35%	35% >DSTI≥30%	DSTI < 30%
1	1.04	-4.0912	-4.1437	-4.1726	-4.2159
2	7.13***	-3.7221	-3.8359	-3.6489	-3.7918
3	2.53*	-3.3120	-3.4128	-3.3420	-3.3463
		Panel B Random effects variances			
		0.02303***	0.03671**	0.02107**	0.04302***
		Panel C Random effects correlations			
	LTV ≥100%	1			
LTV < 100%	DSTI ≥ 35%	0.98	1		
	35% >DSTI≥30%	0.92	0.92	1	
	DSTI < 30%	0.98	0.92	1	1

Figure A.1 Share of loans with initial LTV ≥ 100% per DSTI percentiles

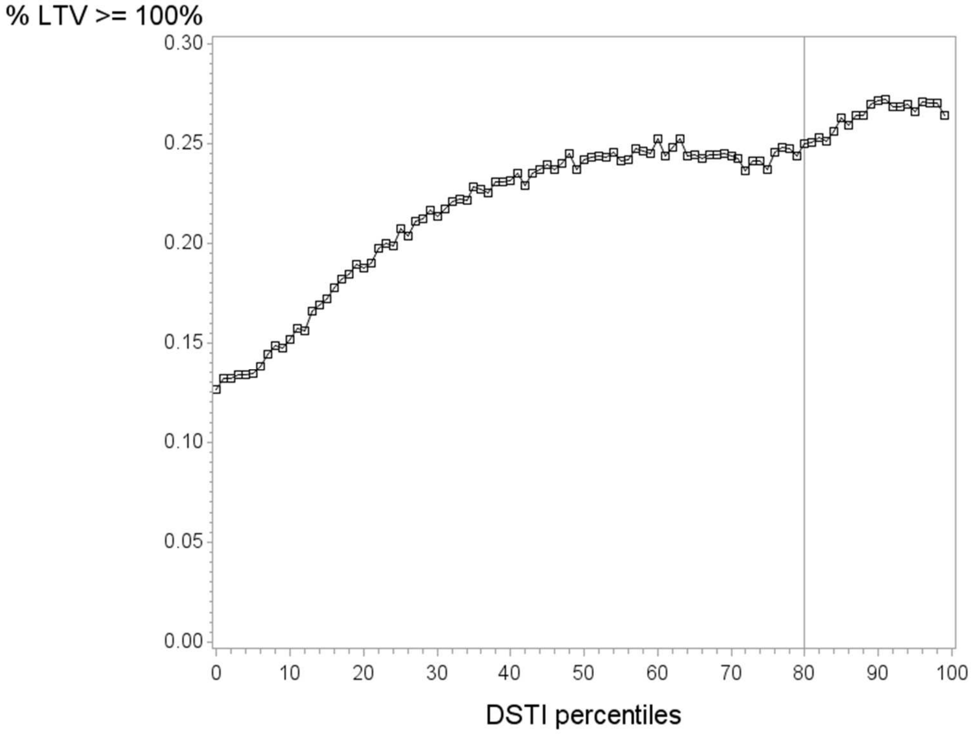


Figure A.1 plots the share of loans with initial LTV ≥ 100% per percentiles of DSTI. The vertical reference line corresponds to a DSTI equal to 35%.