The probability of default for private individuals using microeconomic data. What is the role played by macroprudential measures ?*

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Abstract

Lending to households is central to banking-based financial sectors, but the literature on evaluating the credit risk stemming from this lending activity is still scarce. Our paper contributes to this literature by evaluating the link between household indebtedness and credit risk from the microeconomic perspective. We look at two types of bank loans with different debtor behavior: mortgage and unsecured consumer loans. We use a panel logit model with fixed effects and various control factors. We use credit register data for the Romanian credit market. The main results show that the level of indebtedness (measured by debt-service-to-income ratio), the borrower's credit history and the current occupational status are the main drivers of probability of default for both mortgage and consumer loans. Another result of this paper is that there is a significant non-linear effect of borrower's indebtedness on the probability of default. In addition, we find that macroprudential measures at borrower level implemented at the beginning of the credit cycle played an important role in ensuring a better capacity for debtors to repay their loans.

Keywords: probability of default, household indebtedness, macroprudential measures

JEL Classification: E17, G21

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1 Introduction

Lending to households is central to banking-based financial sectors, but the literature on the main driving factors of households' ability to repay their debt is still scarce. The high level of household indebtedness was one of the main challenges of the recent international financial crises. Therefore, understanding how household financial stress can lead to higher credit risk for banks is essential in improving the existing macroprudential policy framework.

Our paper brings an important contribution to the existing literature by evaluating the link between household indebtedness and credit risk from the microeconomic perspective. We estimate a model for the probability of default for private individuals using debtor-level data based on credit registry information. The model we propose in this paper, by offering an insight into the mechanism through which individuals default on their loans, can be a useful tool for macroprudential policy in various ways. It can help measure the level of systemic risk, assess the transmission channels of policy measures, and improve the design and the calibration of debtor-level macroprudential instruments.

The literature discussing household indebtedness has relied heavily on survey data (regarding main households balance sheet items) up to now and most of them are sensitivity analysis of different indicators of households financial distress (for e.g. financial margin) as evidenced by Johansson and Persson (2006), Herrala and Kauko (2007), Albacete and Lindner (2013), and, more recently, Ampudia et. al (2016). This last paper is part of a still sparse literature on the estimation of probability of default for private individuals, as carried out by Rodriguez and Trucharte (2007), McCarthy (2014) or Kelly and O'Malley (2016).

Another novelty that our paper brings to the existing literature is the distinct exploration of consumer and mortgage loans credit risk. Most of the existing works in this field assess the probability of default by looking at aggregate household debt, without disentangling the borrowers behavior related to mortgage borrowing from that related to borrowing for consumer purposes. To our knowledge, this is the first paper that takes on this kind of challenge. To this aim we construct two separate data samples: one for mortgage loans and another for consumer loans. We estimate separately the probability of default model for these two data samples. The behavior of debtors who have both consumer and mortgage loans is captured only in the in the consumer model where we account for the fact that a borrower also has a mortgage loan; the results indicate that borrowers with both consumer and mortgage loans have a better income situation (given that they were eligible for a mortgage loan) and there is a high chance that the consumer loan may be linked to housing investment.

We run these micro-econometric models on data for the Romanian credit market. The databases that we use contain information such as type of loan (consumer or mortgage), maturity, currency, debtors age, debt-service-to-income ratio and employer type. The model is estimated on half year vintages, spanning the period 2008-2016. This allows us to assess the link over a long period of time, and to further control for time-specific factors which can lead to a debtor's default. We include in our sample loans which are performing at the start of each year, excluding restructured and refinanced loans, and the performance of these loans is assessed over a one year horizon. A loan is considered non-performing if it registers payments which are more than 90 days overdue or if it has been written-off within a year from the moment of analysis.

We estimate the probability of default using a logit model for half-yearly vintages of data, with a debtor-level cross-sectional dimension. The factors we include in our estimations are various indicators regarding the risk profile of the debtor (indebtedness level, age, income) and that of the loan (foreign denominated, maturity). We also use bank, county and year fixed effects (both at origination and at the moment when the household financial fragility is measured). By employing various types of fixed effects we ensure a better identification of the impact of the household indebtedness on credit risk. Finally, we analyze whether there are non-linearities in the impact of the debt-service-to-income ratio on the probability of default by employing a linear and a cubic spline specification.

The results show that the main drivers of high probabilities of default for both mortgage and consumer loans are the level of individual indebtedness (measured by debt-service-to-income ratio) and the income level of the debtor. These results are in line with Hollo and Papp (2007) for Hungary, Kukk (2016) for Estonia and May and Tudela (2005) for Britain who show that debtors that pay a large percentage of their income are more likely to default. Evidence regarding the non-linearity of DSTI points towards a stronger effect for borrowers with DSTI levels above 55 percent. Furthermore, a debtor whose employer is an SME is more likely to default as opposed to one working for a large corporation. As employees at an SME are more likely to face unexpected termination or pay decreases, this supports the findings of McCarthy (2014) for Ireland showing that debtors with fragile employment face a higher likelihood of going into default.

Another aspect that we are interested in is the role of macroprudential measures in reducing the risks stemming from lending to households. We take advantage of the fact that Romania was one of the few countries from Europe that implemented macroprudential measures at the beginning of credit cycle (Cerutti et al., 2017) and we draw from another work that was conducted on efficiency of macroprudential policy in Romania (Epure et al., 2018). To test the efficiency of macroprudential measures we employ four different indexes that captures different sets of measures. Our results indicate that loans granted during periods when macroprudential measures were in place at the beginning of the cycle have a lower probability of default.

These findings can provide the basis for a future development of a stress-test framework which can enable us to better assess the transmission channels of shocks from debtor-level characteristics, particularly household indebtedness, to bank credit risk.

2 Data and Methodology

2.1 Data

We employ data at debtor-level from a variety of sources. We use the same databases for both mortgage and consumer models. We gather most information on loan and debtor characteristics from the NBR Central Credit Registry[1], namely data on residual maturity, age, currency of denomination and loan amount. In the Central Credit Registry we were also able to identify mortgage loans granted through the *First Home* government program. We used the interest rates at bank-level as reported in the NBR Monetary Balance Sheet, which we then merged with our loan-level database, by maturity class, currency and type of loan.

The computation of the debt-service-to-income (DSTI) ratio implied several steps. In order to capture the whole indebtedness level, we took into consideration also the loans reported in the private database of the Credit Bureau. For income we used the wage from tax reports, made available to us by the Ministry of Finance. We computed monthly installments by loan, using the available data on balance sheet loan amount, residual maturity and interest rate, and the

[1]NBR Central Credit Registry covers only loans over 20 000 lei, the equivalent of roughly 4400 euros.

assumption of constant annuity. We limited the range of DSTI values between 5% and 300% by winsorizing extreme values.

From the same tax reports, we calculate also the income group variables and identify the debtors with unrecorded income. For the first set of variables we look at the whole economy income distribution and calculated for each year the minimum and average wage level. Based on these two values we then construct four dummy variables for income groups as follows: (a) Income group = 1: debtors with income below minimum wage (for example, for part-time or seasonal jobs), (b) Income group = 2: debtors with income between minimum wage and average wage, (c) Income group = 3: debtors with income between average wage and twice the average wage, (d) Income group = 4: debtors with income above the twice the average income. In addition, we look at individuals that have loans but are not in the tax reports. We classify these debtors as individuals with unrecorded wage as we cannot assess if they are unemployed, early retired or on other special benefits or on other income arrangements. We expect the majority of these individuals to be unemployed as the percentage of those with legal age for retiring is very small.

Aggregation of loan-level data into debtor-level data is performed differently by type of loan: in the case of mortgage loans we keep only one loan per debtor, while in the case of consumer loans we consolidate the amounts and we take the characteristics of the biggest loan.

Regarding the time dimension, we cover the period 2008-2016 with half-yearly frequency, managing to capture the peak of the economic boom, the recession following the 2008 crisis and the recent economic recovery. Our through-the-cycle approach is also evident from the historical evolution of the non-performing debtors ratio, which exhibits a fairly cyclical dynamics.

Obtaining the final datasets of the two models (mortgage and consumer) required making several assumptions. First, we look at all performing debtors with outstanding loans at a particular semester vintage and we make sure that they are still active in the database one year ahead, so that we can evaluate their credit risk performance. In the case of every vintage we eliminate the following loan categories: i) loans that have undergone some kind of forbearance (restructured or refinanced), and ii) loans flagged as *unlikely to pay* under the European Banking Authority definition of non-performance (starting with the second half of 2015). These adjustments are necessary in order to observe only debtors which have not been contaminated by a type of behavior which is conducive to non-performance. Second, we identify which of the debtors become non-performing 12 months afterwards. We consider that a debtor is non-performing if it has at least one non-performing loan and such a loan is defined as registering more than 90 days overdue payments. In the case of each model, a debtor is considered non-performing only for that particular type of loan: mortgage or consumer.

We develop two separate models for mortgage loans and consumer loans, allowing for debtor overlap between the two. Our desire is to be able to capture elements which are specific to the type of loan considered and which can later support policy making decisions. Regarding the main loan characteristics in our samples, we observe that the median residual maturity of a mortgage loan is currently around 24 years, while in the case of consumer loans it hovers around 3 years. The median interest rate of both mortgage and consumer loans has dropped significantly since the end of 2008, due to the accommodative monetary policy stance, and the median values currently stand at 4% and 10% respectively. These developments have translated in a significant decrease of the median DSTI from its peak values measured in June 2010 (66% to 30% for mortgage loans and 55% to 36% for consumer loans). As expected the median DSTI of non-performing debtors is significantly higher. With respect to the median monthly installment, the amount is similar for mortgage and consumer loans, given that we take into account total indebtedness, and it represents around 35 % of the current average national wage. The share of FX loans exhibited a major adjustment in time, given stricter macroprudential policy measures for FX loans after 2011 and the recent drops in national currency financing. Currently, in our samples, loans denominated in EUR make up 54 % of mortgage credit (down from 75% in 2008) and 4% of consumer credit (down from 33% in 2008). There are no significant differences between EUR denominated loans between performing and non-performing loans. The share of CHF loans has always been smaller, but the trend is similar to that observed in the case of EUR-denominated loans. Non-performing debtors with mortgage loans have higher share of CHF-denominated loans (10% compared to 3% for performing debtors at June 2017), while there are no significant differences for consumer loans.

2.2 Main specifications

The probability of default (PD) is estimated using a pooled logistic regression over the half-yearly vintages starting from second half of 2008 to first half of 2016. This is done separately for the two models, namely for mortgage loans and consumer loans. Our samples have both a cross-sectional and a time dimension, but they are not organized as a panel since we do not intend to follow the same debtor across time. We prefer to pool together half-yearly samples of debtors, by assuming independence of default events across vintages, because this enables us to have a much larger dataset. The sample size is particularly important for us since in the case of mortgage loans we deal with a low-default portfolio. However, by using dummy variables we manage to account for fixed effects for bank, county, time and year of origination.

The logistic regression has become a standard econometric tool for estimation of probabilities for a binary dependent variable. In our case the binary outcome is represented by the default status of a debtor, which is defined as more than 90 days overdue payments for the particular type of loan covered by the model. The estimation implies the assumption of a logistic distribution of the probability of default:

$$p(x) = \frac{e^{f(x)}}{1 + e^{f(x)}} \tag{1}$$

where $f(x)$ represents the linear combination of explanatory variables according to each model. Thus, the logistic transformation (log odds) of the probability of default has the features of a linear regression:

$$f(x) = ln\left(\frac{p(x)}{1 - p(x)}\right) \tag{2}$$

The coefficients which result from the logistic regression do no have a direct interpretation. The contribution of each variable to the estimated probability can be quantified through the computation of marginal effects. These reveal by how much the PD changes as a result of a unit change in the variable of interest.

We evaluate model performance by discriminatory power which we measure by computing the ROC (Receiver Operating Characteristic). The ROC assesses how well predicted probabilities at different thresholds manage to discriminate between good and bad borrowers. The closer its value is to 100 % the better the model is; usually a ROC of over 70 % is indicative of a very high discriminatory power, while a ROC of 50 % is associated with a non-informative random model. The discriminatory power of all models is highly satisfactory. In the case of the baseline model the AR (accuracy ratio) registers values of around 80% for mortgage loans and 70% for consumer loans (See Figure A.1, Appendix A).

We use two main specifications for logistic regressions that fits the main objectives of the paper: assessing the link between borrower's indebtedness level and loans credit risk and, second, testing the ability of macroprudential measures in reducing the probability of default on household loans.

For borrower's characteristics:

$$f_{itk}(x) = \beta_1 * DSTI_{it} + \beta_2 * X_{it} + \beta_3 * Y_{itk} + \beta_3 * Z_t + Bank\_FE + County\_FE + \\ + VintageTime\_FE + OriginationTime\_FE \quad (3)$$

For macroprudential measures:

$$f_{itk}(x) = \beta_0 * MPP_{it_0} + \beta_1 * DSTI_{it_0} + \beta_2 * X_{it} + \beta_3 * Y_{itk} + \beta_3 * Z_t + Bank\_FE + \\ + County\_FE + VintageTime\_FE \quad (4)$$

where k represents the type of loan (mortgage or consumer), i debtor, t vintage time and t_0 origination time, X_{it} are debtor characteristics like age, credit history (previous NPL), income, employer characteristics, Y_{itk} are loan characteristics like FX, residual maturity, *First Home* loan Z_t are macroeconomic factors like GDP, interest rate, inflation, unemployment rate.

The fixed effects on year of origination are important as it allows us to control for factors stemming from banks' credit standards and macroeconomic conditions at the time when the credit was granted. In the second model (for the impact of macroprudential measures) we drop these fixed effects ($OriginationTime\_FE$) as they will otherwise absorb the effects of policy measures.

We build on the core models and evaluate various dimensions of debtor non-performance. First, we look into debtor and loan specific characteristics, DSTI being of particular interest. Second, we evaluate various interactions between DSTI and other relevant variables in order to capture how indebtedness impacts performance differently by currency of denomination of loans and income group of debtors. Third, we assess whether debtors who took loans during periods of macroprudential regulation performed better than those who contracted loans during times with no such regulation. The specifications are virtually the same for mortgage and consumer loans.

2.3 Non-linear impact of DSTI on debtor's performance

We want also to have a closer look at potential non-linear transmission effects of the DSTI level into debtor performance. To this end we created a specification in which we included DSTI intervals as a separated set of variables, alternative to the single DSTI variable. These intervals range from 25% to 65% (with a 10 percentage point step between nodes) and we added an additional interval for DSTI over 100%. We were interested to see if below certain DSTI levels debtors are less prone to default and/or if above certain DSTI levels debtors become significantly riskier. Loans with DSTI above 150% were censored in order to avoid multicollinearity issues for newly created variables.

For robustness purposes, we also developed the above-mentioned set-up following Harrell (2013) into a spline model with two specifications: a linear spline, which creates piecewise linear functions between the segments, and a restricted cubic spline, which allows for a continuous smooth function that creates a piecewise cubic polynomial between knots and a linear interpolation before the first knot and after the last knot.

The linear spline was created using the following formulas:

$$f(X) = \beta_0 + \beta_1 min(X, k_1) + \sum_{i=2}^{n-1} \{max[min(X, k_i), k_{i-1}] - k_{i-1}\} + \beta_n (X - k_n)_+ \tag{5}$$

where: X is the original value, i determines the number of knots, k are the specified knots and n is the number of knots.

The cubic spline variables were created using the following formulas:

$$f(X) = \beta_0 + \beta_1 X + \sum_{i=1}^{n-3} \beta_i (X_{i+1} - k_i)_+ \tag{6}$$

where:

$$X_{i+1} = \frac{(X - k_i)_+^3}{(k_n - k_1)^2} - \frac{\left\{(X - k_{n-1})_+^3 (k_n - k_i) - (X - k_n)_+^3 (k_{n-1} - k_i)\right\}}{(k_n - k_{n-1})(k_n - k_1)^2} \tag{7}$$

The DSTI variable is split into several variables according to the type of spline function chosen (linear or cubic), and these in turn go into the logistic regression. If any of the estimated β coefficients are significant, this indicates the existence of a non-linearity in the impact of the DSTI on the probability of default.

2.4 The impact of macroprudential policy measures

This model can be useful not only to better understand the link between borrowers' indebtedness and credit risk for the household sector, but also to evaluate the effectiveness of borrower level macroprudential measures. We benefit from the fact that Romania introduced such measures early on in the previous credit cycle. The first measures were set in February 2004 and they consisted of explicit caps on DSTI and LTV. The measures were kept in place up to March 2007 when banks were required to define their own limits based on their risk tolerance and on the risk profile of the debtor and the type of loan. Later on, starting October 2011, new measures were implemented for both DSTI and LTV as follows: the measure on LTV established fixed limits differentiated by the currency of denomination of the loan, while the measure regarding DSTI required banks to determine their own maximum limit taking into account specific shocks for interest rate, exchange rate and income. Also, the DSTI measure was implemented for consumer loans only. A detailed framework of how the measures were defined and calibrated is presented in Neagu et al. (2015).

In order to test the effects of the macroprudential measures at borrower level, we define four different variables that capture macroprudential measures[2]: (i) MPP_CCL - a broad index for all the measures that can be liked to macroprudential policy, (ii) MPP_AOR - a narrow index of macroprudential measures that explicitly targeted mortgage loans, (iii) MPP1 - a dummy variable that take the value 1 for all the loans granted during the 2004-2006 measures that targeted borrower's indebtedness and (iv) MPP2 - a dummy variable that take the value 1 for all the loans granted after 2011 (in 2011 a new measure on borrower's indebteness was implemented).

[2]For more details on these indexes please see Table A.2, Appendix A.

3 Results

Looking at the borrower's characteristics we find that the level of indebtedness plays an important role in the decision of defaulting on a loan, but its impact is exceeded by information regarding the borrower's credit history and his/her occupational status. Another interesting result is that the response of the probability of default to the changes in the borrower's indebtedness is nonlinear and varies on loan type (mortgage vs. consumer loans, FX vs. loans denominated in local currency) and income group. These findings lead to the conclusion that macroprudential measures on borrower's indebtedness should target especially those loans that show the highest sensitivity: mortgage loans, and more specifically those in FX currencies.

A second set of results are those regarding the efficiency of the macroprudential measures throughout the credit cycle. We find that macroprudential measures that were introduced during the expansionary phase of the previous credit cycle were able to reduce the probability of default especially in the case of measures targeting borrower's indebtedness. These results complement those from the existing literature on the impact of such measures on risky loans and borrowers. See, for example, Epure et al. (2018) that investigates these topics on the same economy.

In the following part of this section, we will discuss all these results in details. The tables with the estimated models are presented in Appendix B (for borrower's characteristics) and Appendix C (for macroprudential measures efficiency). The tables contain the actual coefficients of logistic regressions and, therefore, are not the marginal effects of the chosen variables[3]. But, given the fact that the average estimated probabilities on both models (mortgage and consumer loans) are low (around 0.06 % for mortgage loans and 4.5 % for consumer loans), the coefficients can be considered as proxies for relative sensitivities to the average estimated probability[4].

3.1 Borrower's characteristics

The borrower's indebtedness (DSTI ratio) stands out as a good predictor of default for both mortgage and consumer loans. Its coefficients are robust across different specifications. Results are presented in Tables B.1, B.2, B.3, B.4 from Appendix B. In the baseline model, a 1 percentage point increase in DSTI would lead to a 0.4% increase in the probability of default for mortgage loans (model 1 from Table B.1, Appendix B) and to a 2.2% increase for consumer loans (model 1 from Table B.3, Appendix B). In relative terms (if we look only at coefficients), the sensitivity of the indebtedness level is higher for mortgage loans compared to consumer loans. Moreover, if we split the DSTI ratio into the two main components (debt service and income) we see that debt service seems to matter more in relative terms for mortgage portfolio (model 2 from Table B.1 and Table B.3, Appendix B). These results are expected given the fact that the mortgage part of the debt service is usually the largest and, therefore, a change in the mortgage debt service will impact more the borrower's monthly debt payments.

Another interesting result is regarding the occupational status[5] (model 3 from Table B.1 and B.3., Appendix B). We find that the mere fact that the borrower is no longer on the payroll of a company increases its probability of default by 0.7 % in the case of a mortgage loan and by

[3]The marginal effects should be calculated as $\beta * p * (1 - p)$, where p is the average estimated probability.

[4]As p is very small, $1 - p$ is closed to 1. Therefore, the marginal effects can be approximated as $m \simeq \beta * p$ and, therefore, $\beta \simeq m/p$.

[5]As we explained in the section 2, the occupational status is captured by a dummy variable that takes the value 1 if the borrower no longer appears in the tax reports from the fiscal authority, i.e. he/she no longer receives wage.

3.6 % for a consumer loan, while the sensitivity to his/her indebtedness level (we look only at the indebtedness level at the origination of the loan, $DSTI_{t0}$ as the debtor no longer receives wage) decreases significantly[6]. Even if the sensitivity on borrower's indebtedness decreases, the overall level of default is higher (see Figure B.2, Appendix B). Moreover, the gap between the average level of non-performance for debtors with unrecorded wage and those with recorded wage is significantly larger in the case of consumer loans (5 times larger than in the case of mortgage loans).

There are no statistically significant differences (especially in absolute terms) regarding the impact of the current level of indebtedness compared to the origination one, but the different factors that drive the current level of indebtedness contribute substantially either positively (in the case of FX and interest rate shocks) or negatively (in the case of income shock) to the level of the default probability (model 5 from Table B.1 and B.3, Appendix B). More specifically, a 1 percentage point increase in the exchange rate adds 0.7 percentage points in the case of mortgage loans and 2 percentage points in the case of consumer loans, while an income change of one percentage point decrease it by 0.2 and, respectively, 1.5 percentage points. In the case of consumer loans, a change in the interest rate is also important.

Income distribution matters, also, for both type of loans. Whether a debtor belongs to a particular income group influences his/her performance with a slight difference between the two type of loans (model 2 from Table B.2 and B.4, Appendix B). People with monthly wage between the minimum and the national average wage are more prone to default on a consumer loan than on a mortgage one, but in both cases the sensitivities on income groups are monotonically decreasing. Higher the income group a debtor is in, higher the quality of the loan, either mortgage or consumer.

An notable contribution to the probability of default for both mortgage and consumer loans is the borrower's credit history (model 1 from Table B.2 and B.4, Appendix B). If the debtor has already defaulted on another loan, the probability to default on the current loan increases by 1.3 and, respectively, 3.8 percentage points. Even more interesting, the increase in the credit risk of mortgage loans comes from a default on a consumer loan[7]. A second type of information that we look at in terms of debtor history is if he/she has another type of loan (i.e. a consumer loan when we assess the mortgage loans probability of default and a mortgage loan for the consumer loans model). In this case, the results differ. In the first case, having at least one consumer loan increases the probability of default by a small amount (only 0.07 percentage points), while in the second case, having a mortgage loans pull downs the probability by 2 percentage points. A possible explanation might be that debtors with a mortgage loan that take also a consumer loan need the additional money to invest in the same house they purchased by credit (for refurbishing it, for example). Therefore, these consumer loans can be associated with debtor's investment needs and have a better quality than other consumer loans that are used for other purposes.

The employer type adds to the factor mix. Being employed by a SME drives up the risk of default by 0.1 and, respectively, 1.3 percentage points depending on the type of loan (model 3 and 4 from Table B.2 and B.4, Appendix B). The impact on consumer loans, in relative terms, is almost double compared with the impact on the mortgage probability of default. We get a somewhat similar result for state owned firm (SOE) employer type. The probability increases by

[6]For the mortgage loans the decrease is 25% as the marginal effect of $DSTI_{t0}$ is 0.4 and that of the interaction term *Unrecorded* $wage_t * DSTI_{t0}$ is -0.1. In the case of consumer loans the impact is 40% (marginal effects are 2.3 and, respectively, -0.9).

[7]This conclusion derives from the way the sample is built for the mortgage model. In our sample, we included all the debtors with only one mortgage loan but possible other consumer loans (the debtors with more than one mortgage loan represent only 3% of the total sample). Therefore, in this case, the second loan is a consumer loan.

0.1 and, respectively, 0.4 percentage points for the two types of credits. This outcome is most probably the consequence of some of the measures taken by the Romanian government after the 2007-2008 international crisis to adjust the public balance (for example, the reduction by 25 % of wages in the public sector).

The *First Home* program appears to be relevant for credit performance: debtors who contracted loans through this program are significantly less risky than the average mortgage loan debtor. The quantitative impact is -1.1 percentage points.

Other more general debtor and loan characteristics have also power in explaining the loan performance. For example, in the case of residual maturity, in the first years of a mortgage loan a debtor is more inclined to default as he/she paid only a small amount of the debt[8]. The link is reversed for consumer loans: longer the residual maturity, lower the risk. A possible explanation of this result is that, usually, consumer loans with longer maturities are associated with housing investments and, therefore, are of a higher quality.

3.1.1 Nonlinear effects of borrower's indebtedness

In order to obtain more depth to our analysis of the link between borrower's indebtedness and loan performance we look at possible asymmetries by loan and borrower riskiness and, also, we test some nonlinear specifications.

First, we assess the response of the probability of default to the level of borrower's indebtedness by currency type (model 1 from Table B.5, Appendix B). The results indicate that mortgage FX loans are more sensitive to the level of DSTI irrespective to the type of the FX currency (by around 40% higher[9]). For consumer loans, the differences between FX and local currency loans are less significant[10].

Second, we investigate the possible asymmetries of DSTI sensitivity for borrowers from different income groups (model 2 from Table B.5, Appendix B). We find that the link between DSTI and the probability of default decreases its importance the lower the income group a debtor is in, while the overall probability increases. A first possible explanation for this outcome is that debtors with lower income might face income shocks with a higher probability than those in upper income groups and that these shocks have a higher impact on their ability to repay the loan than other financial shocks like FX or interest rate shocks. A second explanation is that there might be a non-linear link between the two variables.

We test two non-linear specifications between DSTI and loans performance as we explained in section 2: a linear spline (Table B.6, Appendix B) and a restricted cubic spline (Table B.7, Appendix B). In the case of linear spline, both models (for mortgage and consumer loans) indicate significant non-linear behavior that differs across income groups. For mortgage loans, the highest sensitivities are for DSTI values between 15% and 30% and above 50%. This second result might come for the fact that cosigners are important in obtaining a mortgage loan especially for middle and low income groups. For consumer loans, the highest sensitivities are for DSTI values up to 50%, with some pronounced differences in the case of debtors with income between minimum and average wage.

[8]In the first 5 years a debtors pays around 10% of the mortgage loan under the constant annuity method as the interest is the major part of the debt service.

[9]The marginal effects of the interaction terms of $DSTI_{t0}$ with dummy variables for lei denominated loans (RON) and, respectively EUR denominated loans are 0.22 and 0.3

[10]The marginal effects of the interaction terms of $DSTI_{t0}$ with dummy variables for lei denominated loans (RON) and, respectively EUR denominated loans are 1.5 and 1.4.

For restricted cubic spline specifications, the results show statistical significance only in the case of consumer loans, especially for debtors with income between average and twice the average wage. For these debtors, the highest sensitivity is for DSTI values around 50% (see also Figure B.3, Appendix B).

All these results point to the conclusion of some important non-linear behavior between the level of borrower's indebtedness and the level of loan credit risk, especially for loans around 50% and, in the case of mortgage loans, also for loans that includes also cosigners.

3.2 Macroprudential measures

Romania is one of the few European countries that introduced borrower-level macroprudential measures at the beginning of the previous credit cycle. Were these measures effective in providing debtors a sufficiently high margin to withstand economic and financial shocks, and therefore reduce their probability of default?

To answer this question we test the impact on the probability of default on different macroprudential measuresfootnoteFor more details on these indexes please see Table A.2, Appendix A.. The results are presented in the Tables C.1, C.2, C.3 and C.4. from Appendix C.

A first result is that the macroprudential policy is effective in reducing probability of default on individual loans. We find strong evidence for measures implemented at the beginning of the credit cycle (Tables C.2 and C.4, Appendix C). For example, if we look at the cumulative indexes (MPP_CCL and MPP_AOR) on the mortgage portfolio for the loans granted before 2009, a change by one standard deviation of the policy index decreases the probability of default by 23% (MPP_CCL) and, respectively by 17% (MPP_AOR, models 1 and 2 from Table C.2, Appendix C)[11]. The results on the MPP_CCL index are not significant for consumer loans but this is not a major surprise as most of the macroprudential measures introduced by Romania targeted FX loans (only 28% of consumer loans from our data sample were granted in foreign currencies).

A second important result is that the measures that targeted borrower's indebtedness were the most efficient, as they helped borrowers with either mortgage or consumer loans. Similar to the previous findings, we find evidence for the efficiency of measures introduced at the beginning of the cycle (MPP1). Therefore, the loans granted during this period when caps on borrower's indebtedness were implemented have the probability of default by almost one third lower irrespective of the loan type (mortgage or consumer, model 3 from Table C.2 and model 2 from Table C.4, Appendix C). By contrast, the measures from the last part of the credit cycle (MPP2) are not generating significant statistical results on loans riskiness as, most probable, we have to wait for another cycle as loans granted under these measures did not experienced notable macroeconomic shocks.

4 Conclusions

Our paper brings an important contribution to the existing literature on borrower riskiness by assessing the link between indebtedness and credit risk from the microeconomic perspective. We estimate a model for the probability of default for private individuals using debtor-level data based on credit register information. Another novelty that our paper brings to the existing

[11]The marginal effects of one standard deviation are -0.14 and, respectively, -0.10.

literature is the distinct exploration of credit risk for consumer and mortgage loans. To our knowledge, this is the first paper that takes on these kinds of challenges.

We find that the borrower's indebtedness level plays an important role for the quality of a loan. However, the impact of past credit events and the current occupational status are stronger drivers of the probability of default. Moreover, the response of the probability to the level of indebtedness is nonlinear and varies by the type of credit, the income level and the point on the DSTI curve the debtor is currently at (with highest sensitivities around DSTI values of 50%). These findings lead to the conclusion that macroprudential measures on borrower's indebtedness should target especially those loans that show the highest sensitivity: mortgage loans, and more specifically those in FX currencies.

A third contribution that our paper brings to the literature is on assessing the macroprudential measures efficiency. We do that by assessing the ability of the measures to reduce borrower's riskiness. We find strong evidence for the measures implemented at the beginning of the credit cycle. Moreover, the measures that targeted borrower's indebtedness specifically appear to be the most efficient. For example, the loans granted in the first part of the cycle when caps on borrower's indebtedness were implemented have a probability of default by almost one third lower. By contrast, the measures implemented in the last part of the credit cycle are not showing significant results. Most probable, we have to wait for another cycle as loans granted under these measures did not experienced notable macroeconomic shocks.

Understanding how household financial stress can lead to higher credit risk for banks is essential in order to help improving the existing macroprudential policy framework. The models we propose in this paper can be a useful tool not only for systemic risk measurement, but also for assessing the transmission channels of policy measures, by offering an insight into the mechanism through which individuals default on their loans. The use of these models can then help improve the design and calibration of debtor-level macroprudential instruments.

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Appendix A Data statistics

A.1 General statistics

Variables	Mortgage loans N (mil)	Mean	Median	STD	Consumer loans N (mil)	Mean	Median	STD
Dependent variable	2.89	0.01	0.00	0.08	4.26	0.05	0.00	0.21
Borrower								
Age	2.89	36.34	35.00	7.48	4.26	40.95	40.00	9.74
DSTI t	2.80	0.75	0.46	0.76	4.10	0.74	0.47	0.72
DSTI t0	0.99	1.04	0.67	0.90	2.27	0.78	0.52	0.72
Unrecorded wage	2.89	0.04	0.00	0.17	4.26	0.04	0.00	0.19
Ln Income t	2.80	2.96	3.03	1.02	4.10	2.78	2.86	0.95
Ln Income t0	1.01	2.67	2.76	1.07	2.30	2.65	2.72	0.91
Income group = 1	2.89	0.10	0.00	0.30	4.26	0.08	0.00	0.27
Income group = 2	2.89	0.29	0.00	0.45	4.26	0.33	0.00	0.47
Income group = 3	2.89	0.31	0.00	0.46	4.26	0.36	0.00	0.48
Income group = 4	2.89	0.27	0.00	0.45	4.26	0.19	0.00	0.39
Other loan type t	2.89	0.40	0.00	0.49	4.26	0.09	0.00	0.29
Other NPL(s) t	2.89	0.03	0.00	0.16	4.26	0.03	0.00	0.18
Employer: SME	2.89	0.39	0.00	0.49	4.26	0.30	0.00	0.46
Employer: SOE	2.89	0.04	0.00	0.190	4.26	0.07	0.00	0.25
Loan								
FX	2.89	0.77	1.00	0.42	4.26	0.28	0.00	0.45
Interest rate t	2.89	0.05	0.05	0.02	4.26	0.12	0.11	0.04
RON	2.89	0.23	0.00	0.42	4.26	0.72	1.00	0.45
EUR	2.89	0.70	1.00	0.46	4.26	0.25	0.00	0.43
CHF	2.89	0.06	0.00	0.24	4.26	0.03	0.00	0.17
First Home program	2.89	0.41	0.00	0.49	n.a.	n.a.	n.a.	n.a.
dt0,t FX	2.89	0.09	0.03	0.13	4.26	0.04	0.00	0.09
dt0,t Interest rate	1.07	-0.02	-0.01	0.03	2.34	-0.01	0.00	0.03
dt0,t Income	0.92	0.27	0.14	0.97	2.13	0.08	0.02	0.73
dt0,t RE prices	2.89	-0.32	-0.08	0.81	4.26	-0.49	-0.23	0.86
Macroprudential measures								
MPP_CCL	2.87	8.46	7.00	7.51	4.26	10.70	14.00	7.74
MPP_AOR	2.87	1.59	1.00	1.43	n.a.	n.a.	n.a.	n.a.
MPP1	2.89	0.13	0.00	0.33	4.26	0.07	0.00	0.26
MPP2	2.89	0.32	0.00	0.47	4.26	0.21	0.00	0.41
Macroeconomic variables								
GDP	2.87	2.11	2.07	3.24	4.26	0.49	0.84	4.18
REER	2.87	98.57	99.45	2.82	4.26	99.40	99.84	2.791
Inflation*	2.87	2.70	1.50	1.89	4.26	3.81	4.44	1.98
Unemployment**	2.87	4.66	4.40	2.65	4.26	5.25	5.10	2.74
Ln RE prices**	2.87	0.03	0.01	0.10	4.26	0.07	0.03	0.14

Note: * inflation variable is the core inflation rate (calculated by excluding the impact of administered prices)
** the values are at county level

Source: National Bank of Romania, National Institute of Statistics of Romania, ECB

A.2 Macroprudential measures (selection)[12]

Date	Measures	MPP_CCL*	MPP_AOR**	MPP1***	MPP2***
2004 H1	caps on DSTI for mortgage (35%) and consumer (30%) loans and cap on LTV for mortgage loan (75%)	2	2	1	0
2005 H2	cap on DSTI for total loans of 40%	1	1	1	0
2006 H2	similar restrictions on DSTI and LTV for nonbank financial institutions	1	1	1	0
2007 H1	banks are required to define own eligibility criteria for borrowers (previous caps were removed)	-1	-1	0	0
2008 H2	banks are required to define tougher eligibility criteria for household loans by taking into account interest and exchange rate risk	1	1	0	0
2009 H1	previous requirements were removed for mortgage loans, First Home program was launched, provisioning destructibilities rule for mortgage backed loans	-3	-3	0	0
2011 H2	caps on LTV differentiated on currency of denomination of loans (from 60% to 85%) and caps on DSTI determined for stress conditions based on specific risk factors	1	1	0	1
2012 H2	banks are required to define tougher eligibility criteria on loans in foreign currencies for unhedged nonfinancial companies	1	0	0	1
2015 H1	exception introduced for household loans that were restructured or after FX conversion	-1	-1	0	1

Note: * cumulative index, updated index from Epure et al. (2018) using the methodology proposed by Cerutti et al. (2017)
** cumulative index based on Akinci and Olmstead-Rumsey (2013)
*** dummy variable that takes the value one for the periods with the indicated measures (on borrower indebtedness)

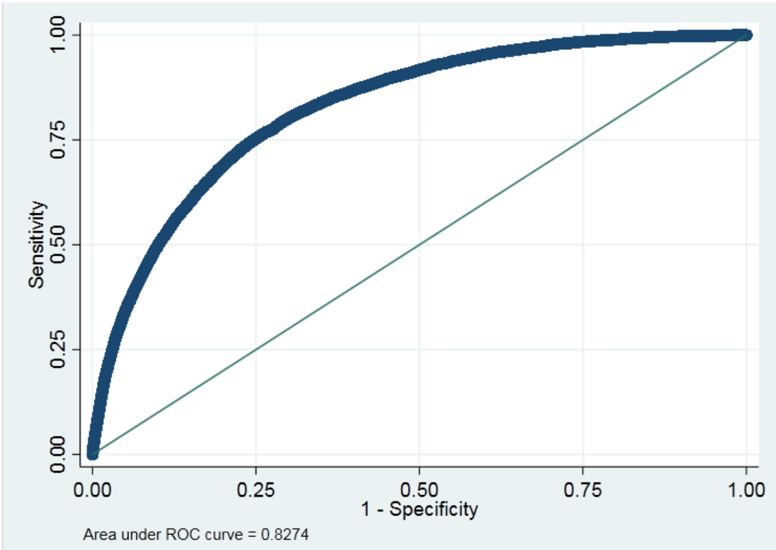
Source: National Bank of Romania

[12]For a detailed list of macroprudential measures implemented by Romania please see Neagu et al. (2015) and Epure et al. (2018).

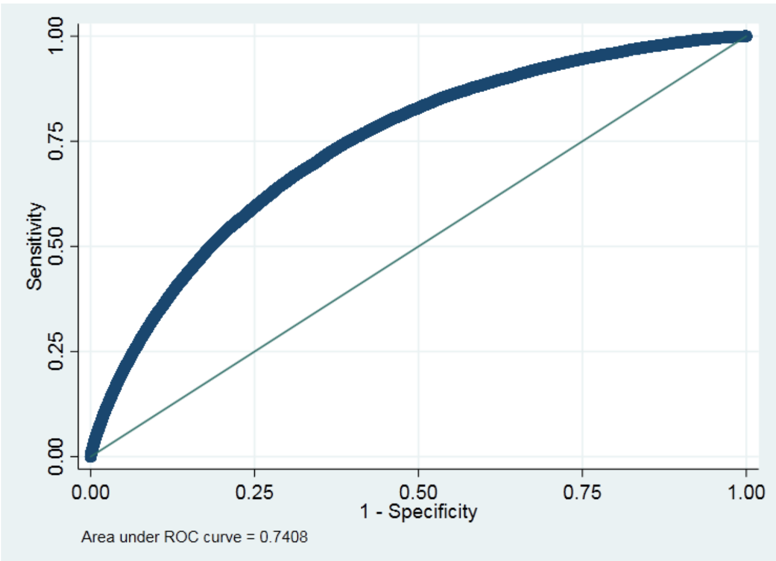
A.3 Discriminatory power of the models

Figure A.1: ROC curve for the baseline models

(a) Mortgage loans



(b) Consumer loans



Note: Sensitivity refers to the share of false signals of default for a particular PD interval, while specificity refers to the share of debtors in a particular PD interval.

Appendix B Results for borrower's characteristics

Table B.1: Mortgage loans - indebtedness and occupational status

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
DSTI t	0.736***				
	(0.000)				
Ln Income t		-0.479***			
		(0.000)			
Ln Debt Service t		0.605***			
		(0.000)			
DSTI t0			0.574***	0.567***	0.674***
			(0.000)	(0.000)	(0.000)
Unrecorded wage t			1.085***		
			(0.000)		
Unrecorded wage t *DSTI t0			-0.229***		
			(0.000)		
dt0,t No other loans					0.025
					(0.582)
dt0,t FX					1.229***
					(0.000)
dt0,t Interest rate					-1.652
					(0.225)
dt0,t RE Index					-0.006
					(0.918)
dt0,t Income					-0.389***
					(0.000)
Observations	2,448,343	2,448,309	817,922	817,922	742,369
Controls	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.130	0.128	0.114	0.109	0.125

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Controls include borrowers' age, residual maturity of the loan, FX, First Home program, GDP, inflation, REER, RE prices and unemployment. The last two variables are at county level.

Table B.2: Mortgage loans - loan history, income and employer type

	Model (1)	Model (2)	Model (3)	Model (4)
DSTI t	0.633***	0.660***	0.705***	0.740***
	(0.000)	(0.000)	(0.000)	(0.000)
Consumer loan(s) t	0.128***			
	(0.000)			
Other NPL(s) t	2.428***			
	(0.000)			
Income group = 2		0.107***		
		(0.000)		
Income group = 3		-0.067**		
		(0.018)		
Income group = 4		-0.516***		
		(0.000)		
Employer: SME			0.193***	
			(0.000)	
Employer: SOE				0.181***
				(0.000)
Borrower age t	0.007***	0.009***	0.008***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
FX loans	0.611***	0.703***	0.681***	0.674***
	(0.000)	(0.000)	(0.000)	(0.000)
First Home program	-2.055***	-2.246***	-2.225***	-2.229***
	(0.000)	(0.000)	(0.000)	(0.000)
Residual maturity	0.027***	0.026***	0.027***	0.027***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,448,343	2,448,343	2,448,343	2,448,343
Macro controls	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes
Pseudo R2	0.192	0.133	0.131	0.130

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Income group are dummy variables that classify debtors according to economy-wide income distribution as follows: (a) Income group = 2: debtors with income between minimum wage and average wage, (b) Income group = 3: debtors with income between average wage and twice the average wage, (c) Income group = 4: debtors with income above the twice the average income. Macro controls include GDP, inflation, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Table B.3: Consumer loans - indebtedness and occupational status

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
DSTI t	0.575***				
	(0.000)				
Ln Income t		-0.475***			
		(0.000)			
Ln Debt Service t		0.267***			
		(0.000)			
DSTI t0			0.466***	0.465***	0.575***
			(0.000)	(0.000)	(0.000)
Unrecorded wage t			0.828***		
			(0.000)		
Unrecorded wage t *DSTI t0			-0.204***		
			(0.000)		
dt0,t No other loans					-0.096***
					(0.000)
dt0,t FX					0.489***
					(0.000)
dt0,t Interest rate					1.159***
					(0.000)
dt0,t RE Index					-0.011
					(0.463)
dt0,t Income					-0.359***
					(0.000)
Borrower age t	-0.030***	-0.029***	-0.025***	-0.025***	-0.028***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FX loans	0.562***	0.595***	0.681***	0.692***	0.543***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residual maturity	-0.026***	-0.021***	-0.020***	-0.021***	-0.025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,112,976	3,112,947	1,621,900	1,621,900	1,498,436
Macro controls	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.0679	0.0701	0.0607	0.0569	0.0667

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Macro controls include GDP, inflation, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

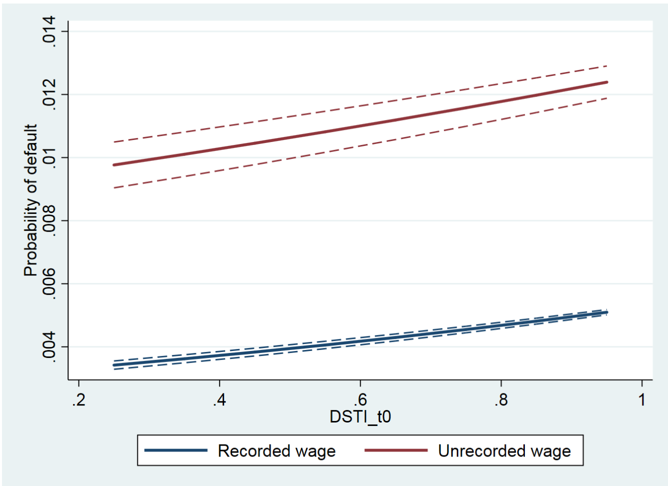
Table B.4: Consumer loans - loan history, income and employer type

	Model (1)	Model (2)	Model (3)	Model (4)
DSTI t	0.528***	0.386***	0.521***	0.579***
	(0.000)	(0.000)	(0.000)	(0.000)
Mortgage loan(s) t	-0.483***			
	(0.000)			
Other NPL(s) t	2.074***			
	(0.000)			
Income group = 2		-0.077***		
		(0.002)		
Income group = 3		-0.534***		
		(0.000)		
Income group = 4		-1.165***		
		(0.000)		
Employer: SME			0.347***	
			(0.000)	
Employer: SOE				0.130***
				(0.000)
Borrower age t	-0.030***	-0.026***	-0.030***	-0.031***
	(0.000)	(0.000)	(0.000)	(0.000)
FX loans	0.460***	0.554***	0.553***	0.563***
	(0.000)	(0.000)	(0.000)	(0.000)
Residual maturity	-0.016***	-0.021***	-0.026***	-0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,112,976	3,112,976	3,112,976	3,112,976
Macro controls	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes
Pseudo R2	0.110	0.0777	0.0708	0.0680

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Income group are dummy variables that classify debtors according to economy-wide income distribution as follows: (a) Income group = 2: debtors with income between minimum wage and average wage, (b) Income group = 3: debtors with income between average wage and twice the average wage, (c) Income group = 4: debtors with income above the twice the average income. Macro controls include GDP, inflation, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Figure B.2: Probability of default by occupational status

(a) Mortgage loans



(b) Consumer loans

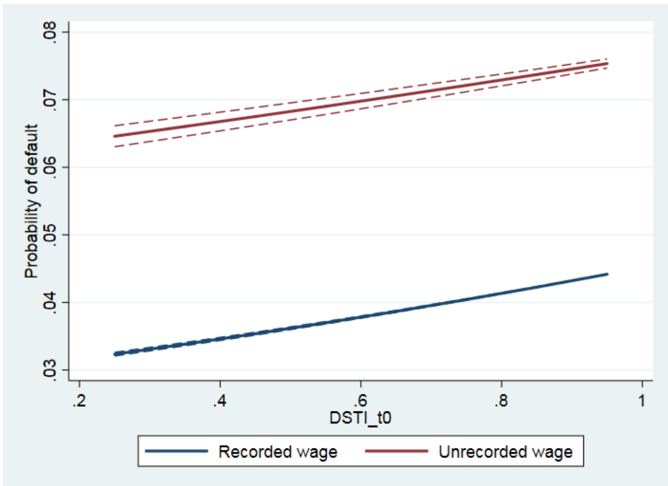


Table B.5: Testing different asymmetries of borrower's indebtedness

	Mortgage		Consumer	
	Model (1)	Model (2)	Model (1)	Model (2)
DSTI t * RON	0.412***		0.403***	
	(0.000)		(0.000)	
DSTI t * EUR	0.569***		0.368***	
	(0.000)		(0.000)	
DSTI t * CHF	0.520***		0.337***	
	(0.000)		(0.000)	
DSTI t * Income group = 1		0.359***		0.113***
		(0.000)		(0.000)
DSTI t * Income group = 2		0.575***		0.449***
		(0.000)		(0.000)
DSTI t * Income group = 3		0.764***		0.569***
		(0.000)		(0.000)
DSTI t * Income group = 4		0.970***		0.735***
		(0.000)		(0.000)
Income group = 1	0.373***	1.005***	0.529***	1.319***
	(0.000)	(0.000)	(0.000)	(0.000)
Income group = 2	0.288***	0.401***	0.453***	0.492***
	(0.000)	(0.000)	(0.000)	(0.000)
Income group = 3	-0.498***	-0.558***	-0.615***	-0.663***
	(0.000)	(0.000)	(0.000)	(0.000)
EUR	0.275***	0.490***	0.529***	0.485***
	(0.000)	(0.000)	(0.000)	(0.000)
CHF	0.976***	1.096***	0.680***	0.627***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,448,343	2,448,343	3,112,976	3,112,976
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Pseudo R2	0.136	0.139	0.0780	0.0796

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Income group are dummy variables that classify debtors according to economy-wide income distribution as follows: (a) Income group = 1: debtors with income below minimum wage (for example, for part-time or seasonal jobs), (b) Income group = 2: debtors with income between minimum wage and average wage, (c) Income group = 3: debtors with income between average wage and twice the average wage, (d) Income group = 4: debtors with income above the twice the average income. Control variables include borrowers' age, FX dummy variable, First Home program dummy variable, residual maturity, GDP, inflation, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Table B.6: Non-linear response of borrower's indebtedness - linear splines

Income	All	Income group = 2	Income group = 3	Income group = 4
Mortgage loans				
DSTI lin 0% - 15%	2.601	2.923	-0.751	-0.648
	(0.100)	(0.742)	(0.828)	(0.736)
DSTI lin 15% - 30%	4.331***	2.127*	1.171*	4.641***
	(0.000)	(0.086)	(0.064)	(0.000)
DSTI lin 30% -50%	1.787***	0.027	0.662	3.010***
	(0.000)	(0.951)	(0.122)	(0.000)
DSTI lin 50% -95%	1.594***	1.065***	1.747***	1.514***
	(0.000)	(0.000)	(0.000)	(0.000)
DSTI lin >95%	0.505***	0.557***	0.967***	0.086
	(0.000)	(0.000)	(0.000)	(0.816)
Observations	2,146,131	615,243	769,182	690,441
Consumer loans				
DSTI lin 0% - 15%	4.525***	4.518***	3.244***	4.516***
	(0.000)	(0.000)	(0.001)	(0.000)
DSTI lin 15% - 30%	5.063***	-0.925**	1.834***	2.995***
	(0.000)	(0.044)	(0.000)	(0.000)
DSTI lin 30% -50%	2.062***	-0.413***	1.786***	2.809***
	(0.000)	(0.003)	(0.000)	(0.000)
DSTI lin 50% -95%	1.176***	0.950***	1.220***	0.844***
	(0.000)	(0.000)	(0.000)	(0.000)
DSTI lin >95%	0.478***	0.489***	0.339***	-0.033
	(0.000)	(0.000)	(0.001)	(0.801)
Observations	2,759,407	901,628	1,150,641	655,211
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Note: The values from the table are the coefficients of the logistic regression with robust probability values in parentheses. Income group variables classify debtors according to economy-wide income distribution as follows: (a) Income group = 2: debtors with income between minimum wage and average wage, (b) Income group = 3: debtors with income between average wage and twice the average wage, (c) Income group = 4: debtors with income above the twice the average income. Control variables include borrowers' age, FX loans, First Home program, residual maturity, GDP, inflation, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

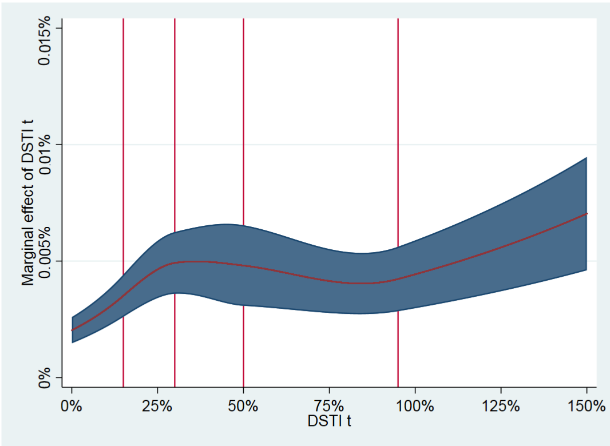
Table B.7: Non-linear response of borrower's indebtedness - cubic splines

Income	All	Income group = 2	Income group = 3	Income group = 4
Mortgage loans				
DTI cub1	3.646***	1.708*	0.192	3.338***
	(0.000)	(0.058)	(0.747)	(0.001)
DTI cub2	-5.628***	-5.016	5.381	0.870
	(0.005)	(0.291)	(0.160)	(0.883)
DTI cub3	7.676**	9.352	-9.685	-6.397
	(0.038)	(0.292)	(0.192)	(0.568)
Observations	2,146,131	615,243	769,182	690,441
Consumer loans				
DTI cub1	4.949***	1.812***	-1.062***	3.415***
	(0.000)	(0.000)	(0.000)	(0.000)
DTI cub2	-12.361***	0.643	6.253***	-3.269
	(0.000)	(0.548)	(0.000)	(0.102)
DTI cub3	19.736***	-3.145	-10.513***	1.837
	(0.000)	(0.130)	(0.001)	(0.644)
Observations	2,759,407	1,150,641	901,628	655,211
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Origination FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

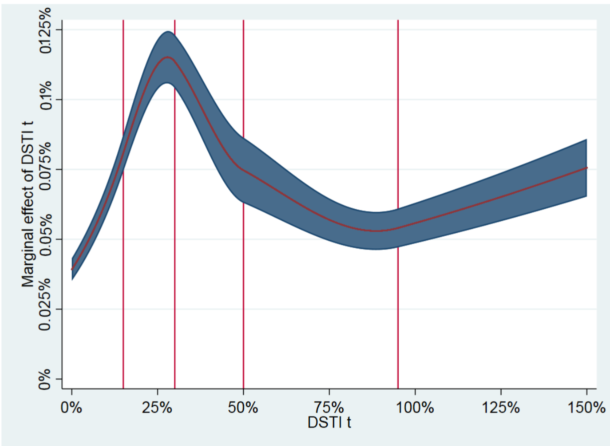
Note: The values from the table are the coefficients of the logistic regression with robust probability values in parentheses. Income group variables classify debtors according to economy-wide income distribution as follows: (a) Income group = 2: debtors with income between minimum wage and average wage, (b) Income group = 3: debtors with income between average wage and twice the average wage, (c) Income group = 4: debtors with income above the twice the average income. Control variables include borrowers' age, FX loans, First Home program, residual maturity, GDP, inflation, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Figure B.3: Non-linear response of the probability of default - cubic splines

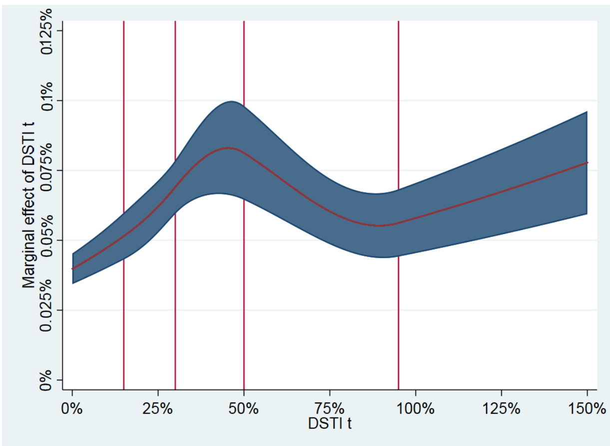
(a) Mortgage loans - all borrowers



(b) Consumer loans - all borrowers



(c) Consumer loans - Income group = 3[a]



[a]debtors with income between average wage and twice the average wage

Appendix C Macroprudential policy efficiency

Table C.1: Mortgage loans - all loans

All loans	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
MPP_CCL	-0.005**					
	(0.022)					
MPP_AOR		-0.007				
		(0.444)				
MPP1			-0.379***			
			(0.000)			
MPP2			0.067			
			(0.239)			
MPP_CCL * DSTI t0				-0.003**		
				(0.011)		
MPP_AOR * DSTI t0					-0.009	
					(0.100)	
MPP1 * DSTI t0						-0.147***
						(0.000)
MPP2 * DSTI t0						0.020
						(0.510)
DSTI t0	0.596***	0.572***	0.583***	0.658***	0.659***	0.591***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	817,922	817,922	817,922	742,369	742,369	742,369
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Origination FE	No	No	No	No	No	No
Pseudo R2	0.107	0.106	0.107	0.120	0.120	0.109

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Control variables include borrowers' age, FX loans, First Home program, residual maturity, GDP, inflation, interest rate, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Table C.2: Mortgage loans - loans granted before 2009

Loans granted before 2009	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
MPP_CCL	-0.031***					
	(0.000)					
MPP_AOR		-0.120***				
		(0.000)				
MPP1			-0.380***			
			(0.000)			
MPP_CCL * DSTI t0				-0.011***		
				(0.000)		
MPP_AOR * DSTI t0					-0.042***	
					(0.007)	
MPP1 * DSTI t0						-0.144***
						(0.000)
DSTI t0	0.563***	0.552***	0.571***	0.746***	0.686***	0.591***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	485,516	485,516	485,516	485,516	485,516	485,516
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Origination FE	No	No	No	No	No	No
Pseudo R2	0.0899	0.0892	0.0908	0.0896	0.0891	0.0903

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Control variables include borrowers' age, FX loans, First Home program, residual maturity, GDP, inflation, interest rate, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Table C.3: Consumer loans - all loans

All loans	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
MPP_CCL	-0.001					
	(0.590)					
MPP1		-0.675***				
		(0.000)				
MPP2			0.026			
			(0.313)			
MPP_CCL * DSTI t0				0.000		
				(0.819)		
MPP1 * DSTI t0					-0.158***	
					(0.000)	
MPP2 * DSTI t0						-0.022**
						(0.036)
DSTI t0	0.445***	0.465***	0.465***	0.440***	0.474***	0.446***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,621,900	1,621,900	1,621,900	1,621,900	1,621,900	1,621,900
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes
Origination FE	No	No	No	No	No	No
Pseudo R2	0.0552	0.0569	0.0569	0.0552	0.0559	0.0552

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Control variables include borrowers' age, FX loans, First Home program, residual maturity, GDP, inflation, interest rate, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.

Table C.4: Consumer loans - loans granted before 2009

Loans granted before 2009	Model (1)	Model (2)	Model (3)	Model (4)
MPP_CCL	-0.010			
	(0.132)			
MPP1		-0.319***		
		(0.000)		
MPP_CCL * DSTI t0			-0.009**	
			(0.014)	
MPP1 * DSTI t0				-0.166***
				(0.000)
DSTI t0	0.463***	0.478***	0.616***	0.497***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,096,167	1,096,167	1,096,167	1,096,167
Controls	Yes	Yes	Yes	Yes
Banks FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Vintage FE	Yes	Yes	Yes	Yes
Origination FE	No	No	No	No
Pseudo R2	0.0479	0.0489	0.0480	0.0487

Note: The values from the table are the coefficients of the logistic regressions with robust probability values in parentheses. Control variables include borrowers' age, FX loans, First Home program, residual maturity, GDP, inflation, interest rate, REER (real effective exchange rate), real estate prices and unemployment. The last two variables are at county level.