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Analysis of the Impact of Borrower-Based Measures*

Martin Cesnak[a], Ján Klacso[b], Roman Vasil'[c]

Abstract

The National Bank of Slovakia has been actively implementing borrower-based measures since 2014. In this paper we provide a cost-benefit analysis of these measures. DSTI measures affected mainly the riskiest borrowers with at most secondary education and lower income. Exemptions from DTI limits are provided mainly to borrowers with a higher volume of loans and higher education. LTV limits affected mainly younger borrowers up to 35 years old. The impact of respective measures was affected by front-loading, by the gradual tightening of the limits and by other legislative changes. The highest impact is estimated in 2019, when the volume of newly granted loans was lowered by 17% due to the measures. The estimated impact on residential real estate prices is relatively mild. The current coronavirus pandemic is the first period when systemic risks could have materialized after the implementation of the measures. Due to the possible loan payment deferral the number of loans defaulted has remained relatively low, therefore LTV measures have not been able to limit credit losses. On the other hand, DSTI measures have helped to mitigate credit risk. Households affected the most by the pandemic were those with an already high debt burden even before the outbreak of the crisis. These households have used loan payment deferral to a larger extent.

JEL codes: C58, D61, G21, G28

Keywords: borrower-based measures, cost-benefit analysis, LTV, DTI, DSTI

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1. Introduction

Retail loans granted by Slovak banks have been growing fast for years. Unlike in most countries of Central and Eastern Europe, housing loans recorded double-digit annual growth rates even after the great financial crisis, having its highest impact in 2009. Simultaneously, households' indebtedness has been increasing as well. Currently it exceeds the levels of most countries in the region.

Therefore, the National Bank of Slovakia (NBS) has been gradually implementing and tightening borrower-based measures (BBMs) since 2014. Currently a comprehensive set of borrower-based measures is implemented in the field of (i) loan-to-value ratio (LTV), (ii) debt service-to-income ratio (DSTI) and (iii) debt-to-income ratio (DTI).

LTV, DSTI and DTI limits decrease credit risk in the banks' loan portfolios. Measures are aimed at preventing the excessive cumulation of systemic risks during the expansionary phase of the credit cycle. The growing interest in these measures makes it necessary to assess their possible unintended consequences, mainly during "normal" times. Excessive negative impact on residential real estate prices, decreasing accessibility to credit for some potential borrowers or the shift of credit provision to non-regulated segments are among the most frequently discussed possible unintended consequences[1].

The aim of the paper is to provide a complex cost-benefit analysis of the BBMs implemented by the NBS. We study the impact of measures on debtors, on the volume and riskiness of retail loans and on residential real estate prices. As the provision of credit in 2020 was affected by the pandemic, we are focusing on loans granted until end-2019.

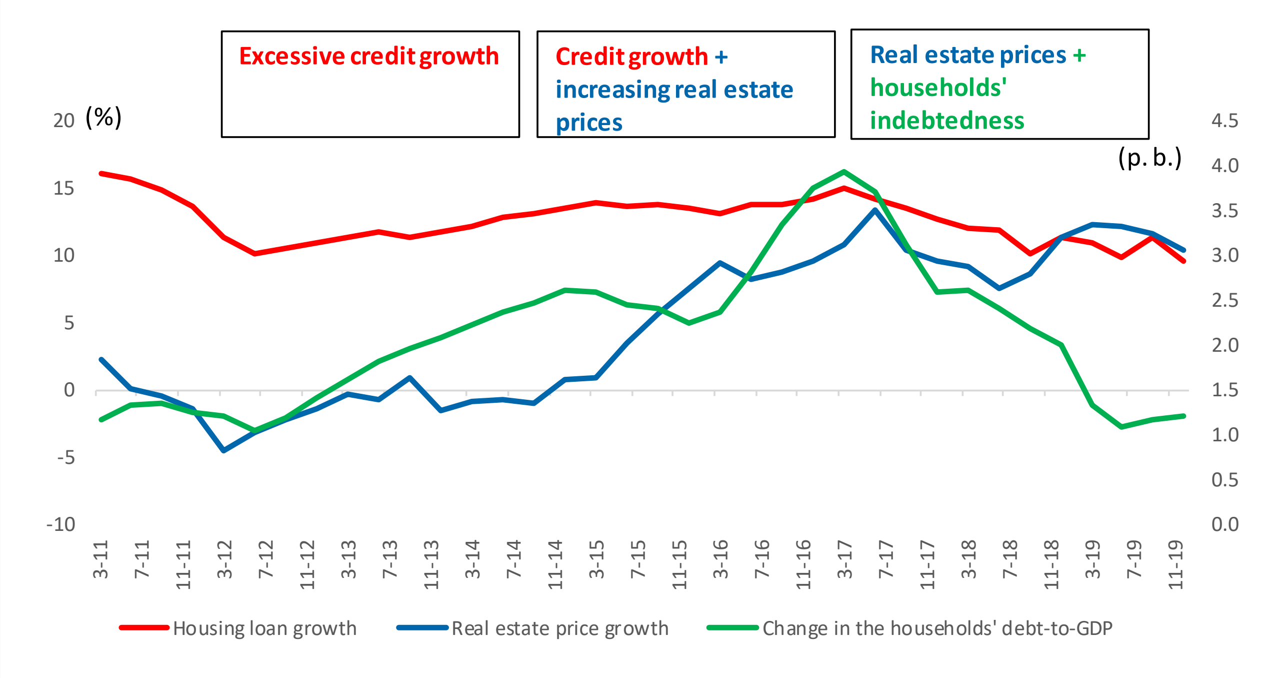
The paper is divided into eight sections. The next section gives a brief overview of the measures implemented. Section 3 summarizes the current state of the art about the impact of BBMs on the financial sector and the real economy. Section four analyses the impact of BBMs on the availability of credit. Section five estimates the impact of BBMs on the supply of credit. The following section assesses the impact of BBMs on the volume of newly granted loans. Section seven describes the relationship between BBMs and residential real estate prices. Section eight assesses the impact of BBMs during periods of increased tensions in the real economy. The last section concludes.

[1] Whether the impact of borrower-based measures, inter alia, on residential real estate prices or accessibility of credit is an advantage or disadvantage is a complicated question. It depends on the actual phase of the credit cycle, on the amplitude and duration of the impact and on many more factors.

2. Overview of BBMs

The NBS has been implementing BBMs since end-2014 for several reasons (Chart 1). The annual growth rate of retail loans was for years the highest among all EU countries (NBS, 2014). Since 2015, this trend has been complemented also by increasing residential real estate prices. Finally, the increasing volume of loans translated into growing households' indebtedness. The latter was identified as one of the main systemic risks for the Slovak banking sector (NBS, 2019). These different reasons have led to different goals aimed by respective phases of implementation and tightening of BBMs. An overview of these goals is described in Harrison et al. (2018).

Chart 1 Factors affecting the implementation of borrower-based measures



Source: NBS.

Different limits have been imposed. In 2014, an LTV and DSTI limit, a maximum maturity for housing as well as consumer loans and an interest rate shock was introduced in the form of a recommendation. Since 2017 the recommendation has been transformed into binding legislation. LTV and DSTI limits have been gradually tightened and a DTI limit was implemented. The gradual tightening of LTV, DSTI and DTI limits is shown in Table 1.

Table 1 Overview of the most important borrower-based measures implemented by the NBS

		LTV		DSTI		DTI	
		Maximum	Exception	Maximum	Exception	Maximum	Exception
Recommendation	11-14	100%	25% between 90% - 100%				
	3-15			100%			
	7-15		20% between 90% - 100%				
	1-16						
	4-16		15% between 90% - 100%				
NBS Decree	1-17		10% between 90% - 100%, 50% between 80% - 100%	Specification of the definition of DSTI			
	3-17			95%			
	7-17		10% between 90% - 100%, 40% between 80% - 100%	90%			
	1-18			85%			
	7-18	90%	35% between 80% - 90%	80%		8 years	Exception 20%
	10-18		30% between 80% - 90%				Exception 15%
	1-19		25% between 80% - 90%				Exception 10%
	7-19		20% between 80% - 90%				Exception 5% + 5% for young borrowers
	1-20			60%	15% between 60% a 80%		
	4-20				5% between 60% a 80%		
	7-20				5% between 60% a 70%		

Source: NBS.

3. Impact of borrower-based measures

After the great financial crisis and the subsequent sovereign crisis, there has been an increasing use of borrower-based measures also in the EU.[2] Increasing interest in the implementation of these measures creates a need to assess not only their benefits, but also their possible costs/unintended consequences.

Limits on BBMs are usually implemented during the expansionary phase of the credit cycle. On the one hand, limits prevent excessive credit growth or the excessive growth of households' indebtedness. On the other hand, they mitigate adverse impact on banks and debtors in case of negative shock, when cumulated risks can materialise. One of the main arguments for implementing BBMs is that loans granted during the expansionary phase of the credit cycle with higher LTV, DSTI or DTI ratios can lead to cumulation of systemic risks and cause higher credit losses during downturns (Cassidy and Hallissey, 2016).

Empirical analysis confirms a link between BBMs and credit growth or real estate prices. Richter et al. (2018), Vandenbussche et al. (2015), Ahuja and Nabar (2011) or Igan and Kang (2011) shows, on a relatively large sample of countries, that imposing LTV and/or DTI limits reduce housing loans growth and consequently also real estate price growth. Kuttner and Shim (2012) concluded that tightening of DSTI affects more the volume of loans while tightening of LTV affects more real estate prices.

The impact of BBMs on the riskiness of retail loans is equally important. Cassidy and Hallissey (2016) or Gross and Población (2017) concluded that BBMs are efficient in mitigating losses stemming from the retail loan portfolio by decreasing the probability of default as well as the loss given default.

The implementation of BMMs can, however, have some unintended consequences as well. Some of these consequences have already been discussed by other central banks having implemented such measures (e.g. v Cassidy and Hallissey, 2016). In case of LTV and LTI limits applied on housing loans the following points are discussed:

- switch in lending to other, non-regulated segments;
- larger use of unsecured borrowing to top-up housing loans in case the maximum amount of housing loan is capped and under the value of the collateral;
- easing appraisal standards to increase the value of collateral due to tighter LTV limits;
- front-loading of lending before the introduction/tightening of the measures;
- impact on the rental market – the postponement of buying a property due to LTV limits or lowering the base of possible debtors that can ask for a loan can create pressure on rental prices;
- some of the potential debtors can be out of the lending market because of tighter measures.

The design of BBM limits imposed by the NBS already addresses some of the above points:

- in Slovakia both banks and non-bank credit institutions are regulated by the NBS. The size of the non-regulated market providing credit to retail customers is therefore marginal;
- DTI, DSTI limits and maturity limits are applied both for collateralised and uncollateralised loans. It means that top-up due to LTV limits is possible only if the

[2] An overview of implemented measures is available e.g. on the website of the European Systemic Risk Board: https://www.esrb.europa.eu/national_policy/other/html/index.en.html

debtor satisfies both DSTI and DTI limits, while the maximum maturity of 8 years in case of consumer loans limits the possibility of excessively increasing overall unsecured debt;
- principles for sound collateral appraisal standards are part of the measures;
- in Slovakia the rental market is in general less developed, except in the capital city, Bratislava. The rental market is used by specific customers (students, short-term renters) and therefore it is not an alternative to owing a property in the long-term. Due to the very high preference for owning a property, the impact on this market is expected to be only short-term and lower compared to more advanced economies with a more developed rental market and higher labour mobility;
- front-loading is a specific phenomenon that occurs when the implementation or tightening of limits is known ex ante. Front-loading in Slovakia is possible due to the legislative process of implementing NBS decrees. Such a front-loading is documented and discussed, e.g., in the NBS (2017).

The most important remaining issues connected to the implementation of BBMs are:
- impact on the riskiness of loans;
- impact on the development of the volume of loans (impact on both the demand and supply side) and on the growth of households' indebtedness;
- identification of the group of potential debtors affected the most by the measures;
- impact on the residential real estate market.

4. Impact of BBMs on the accessibility of loans

This section is dedicated to the potential borrowers affected the most by the measures and detects which limits have been the most constraining. For this question, we use the distribution of debtors before and after the implementation of the measures, as well as econometric analysis of the characteristics of the debtors under and above respective limits.

4.1. DSTI limits

The introduction of a 100% DSTI limit affected only a negligible number of loans. In 2014, up to 1% of loans were granted with DSTI above this limit. The gradual tightening to 80% in 2017 was more constraining, as in 2016 almost 10% of debtors got a loan with DSTI above this limit. The most constraining seems to be the limit 60%, as in 2019 altogether 27% of debtors got a loan with DSTI above this limit.

The tightening is visible also on the gradual shift of distribution[3] based on DSTI (Appendix 2) to the "left", i.e. to lower maximum values. Based on the concentration of the distribution around the imposed limits, not all potential borrowers having a loan with a DSTI above the limit refused to take a loan. Some of these potential borrowers decided to ask for a loan with a DSTI close to the imposed limits.

The distribution of debtors before the tightening of limits gives us some characteristics of debtors potentially constrained by the limits. Distribution based on education[4] (Table 2) shows that loans with DSTI above the limits set in the following periods (100% in 2014, 80% in 2016 and 60% in 2019) were granted predominantly to borrowers with lower, mainly secondary education, as the share of borrowers with tertiary education was lower in the group of debtors

[3] Distributions and the consequent analysis include both housing and consumer loans.
[4] We looked also at distribution of loans based on other characteristics like income source, age, or overall debt. We provide only results of the most important characteristics for the respective limits.

above the limits than in the group of debtors under the consequent limits. Further, it seems that loans with higher DSTI were granted mainly to borrowers with lower income[5] (Chart 2). The average income of debtors with loans having DSTI above the consequent limits is lower in each year than the average income of borrowers under the DSTI limits.

Table 2 Distribution of newly granted loans based on DSTI and education

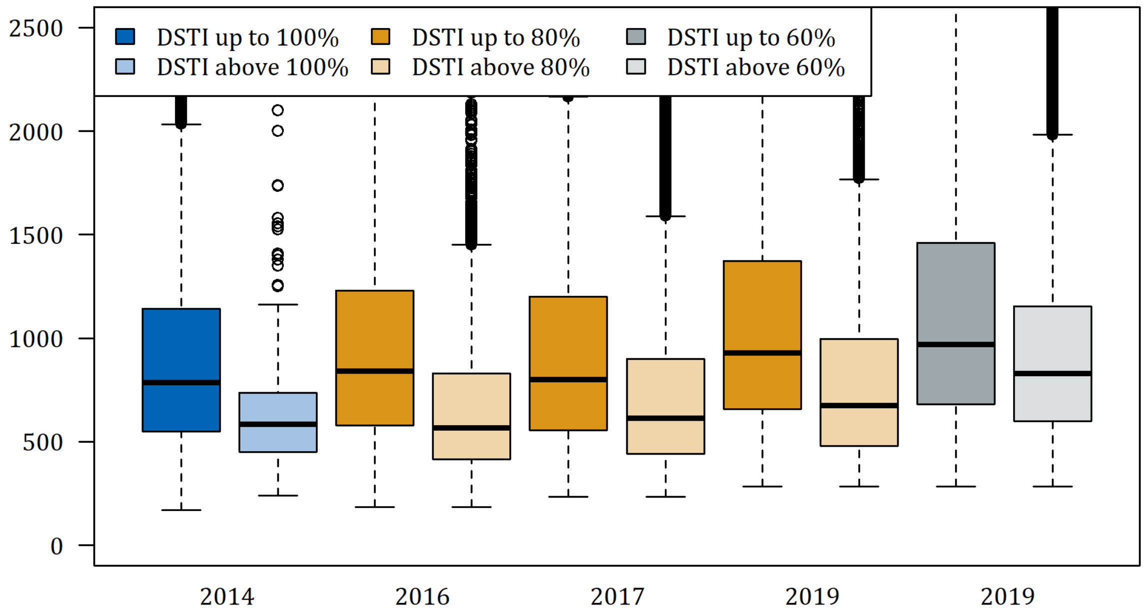
	Highest education of borrowers			
	Number (share)	At most primary	At most secondary	Tertiary
2014 up to100	56 634	4 800	38 285	13 549
	(100%)	(8%)	(68%)	(24%)
2014 above 100	165	7	132	26
	(0%)	(4%)	(80%)	(16%)
2016 up to 80	105 166	6 475	74 189	24 502
	(91%)	(6%)	(71%)	(23%)
2016 above 80	10 228	532	8 273	1 423
	(9%)	(5%)	(81%)	(14%)
2017 up to 80	174 578	6 213	128 727	39 638
	(90%)	(4%)	(74%)	(23%)
2017 above 80	19 075	722	14 599	3 754
	(10%)	(4%)	(77%)	(20%)
2019 up to 80	331 816	10 143	245 272	76 401
	(98%)	(3%)	(74%)	(23%)
2019 above 80	5 611	418	4322	871
	(2%)	(7%)	(77%)	(16%)
2019 up to 60	246 239	7 049	179 478	59 712
	(73%)	(3%)	(73%)	(24%)
2019 above 60	91 188	3 512	70 116	17 560
	(27%)	(4%)	(77%)	(19%)

Source: NBS.

Econometric analysis confirms the importance of income and education. Logit regressions do not reject the impact of education and income on the probability that a given borrower has a loan with DSTI above the consequent limits. (Appendix 3). It means that if at least one borrower has tertiary education, the probability of having a loan with high DSTI, even exceeding the potential limits, is lower than for borrowers with lower education. Also, based on regression results, if the borrower with the highest income is self-employed, there is a higher probability that the loan is granted with higher DSTI above potential limits.

[5] Data are available for regularly received net income of the borrowers.

Chart 2 Distribution of newly granted loans based on DSTI and income



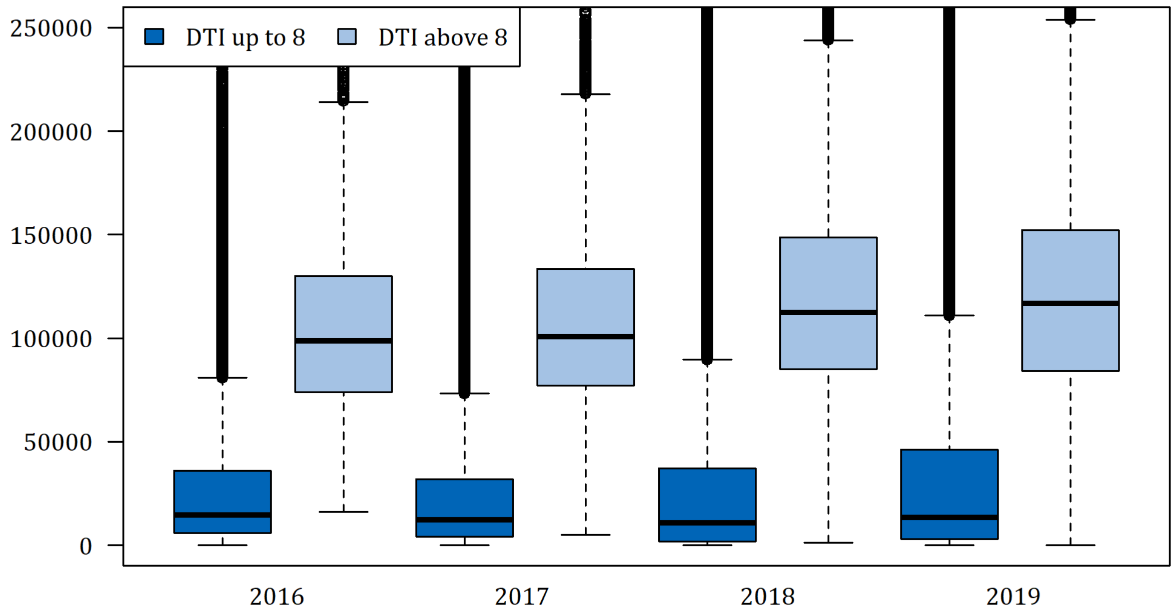
Source: NBS.
Note: Income in EUR is shown in the y-axes.

Decision trees were used as well to confirm the importance of income (Appendix 4). These trees confirmed that before imposing the DSTI limit of 80%, loans with higher DSTI were granted mainly to borrowers with income up to 500 – 600 EUR.

4.2. DTI limits

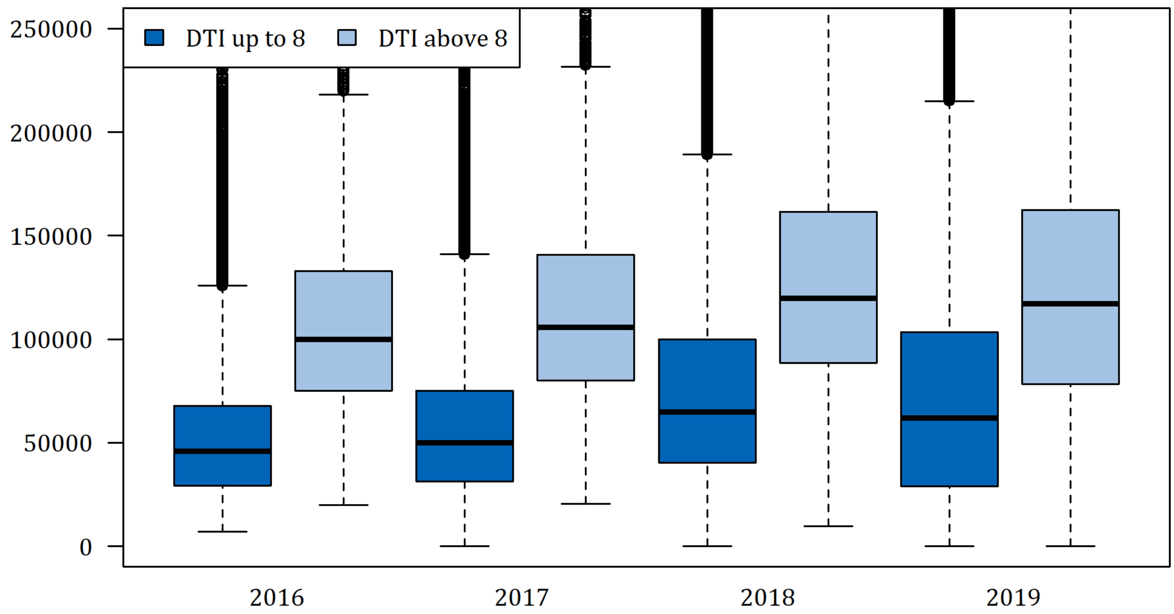
The DTI limit was introduced mainly due to the excessive growth of households' indebtedness. Limit at the level of 8 was introduced as of 1 July 2018 with a gradual tightening of exceptions. In 2017, the last year before the implementation of the DTI limit, loans exceeding the consequent limit were granted to 4% of debtors. The suitability of this limit to cope with increasing indebtedness is confirmed also by the distribution of loans based on DTI, as in general loans with DTI exceeding 8 are granted to customers with higher overall debt. This holds true not only when looking at all debtors (Chart 3), but even when looking at debtors having at least one housing loan (Chart 4). The share of debtors with tertiary education in the volume of loans with DTI exceeding the limit is in each year higher than the share of debtors with tertiary education in the volume of loans with DTI up to the limit. This holds true for all debtors (Table 3) as well as for debtors with at least one housing loan (Table 4). In the case of the latter, in 2019, the share of debtors with tertiary education and DTI above 8 exceeded even the share of debtors with secondary education and DTI above 8. In the case of all debtors, median income is higher for debtors with DTI exceeding 8 (Chart 5). However, this does not hold for debtors having at least one housing loan (Chart 6). It means that limits could have affected potentially larger housing loans. The distribution of loans based on DTI has not changed significantly in the years after the implementation of limits; the right-end of the distribution moved towards lower values (Appendix 5). Regression analysis using newly granted loans to debtors having at least one housing loan confirms the importance of overall debt (Appendix 6). Education enters the regressions, in line with the tables below, with a significant positive coefficient in 2019 in case of all specifications. Decision trees for 2017 and for debtors with at least one housing loan confirm the importance of income and debt (Appendix 7). Debtors with income up to 900 – 1,400 EUR and debt exceeding 50 – 100 thousand EUR have a higher probability of exceeding DTI 8.

Chart 3 Distribution of newly granted loans based on DTI and loan volume – all debtors



Source: NBS.
Note: Loan volume in EUR is shown in the y-axes.

Chart 4 Distribution of newly granted loans based on DTI and loan volume – debtors with at least one housing loan



Source: NBS.
Note: Loan volume in EUR is shown in the y-axes.

The DTI limit was implemented with possible exceptions. Based on distributions after the implementation, banks granted loans within the exceptions mainly to borrowers with tertiary education. The share of borrowers having tertiary education exceeding the limit significantly increased after the implementation of this limit. On the other hand, when looking only at debtors having at least one housing loan, the average volume of loans has not increased since the implementation.

Table 3 Distribution of newly granted loans based on DTI and education – all debtors

	Highest education of borrowers			
	Number (share)	At most primary	At most secondary	Tertiary
2016 up to 8	96 906	6 971	72 891	17 044
	(96%)	(7%)	(75%)	(18%)
2016 above 8	3 932	11	2 506	1 415
	(4%)	(0%)	(64%)	(36%)
2017 up to 8	157 729	6 670	123 591	27 468
	(96%)	(4%)	(78%)	(17%)
2017 above 8	6 040	14	4 009	2 017
	(4%)	(0%)	(66%)	(33%)
2018 up to 8	286 170	11 548	220 780	53 842
	(97%)	(4%)	(77%)	(19%)
2018 above 8	9 474	27	5 637	3 810
	(3 %)	(0%)	(59%)	(40%)
2019 up to 8	330 954	10 641	246 919	73 394
	(98%)	(3%)	(75%)	(22%)
2019 above 8	6 562	28	3 358	3 176
	(2%)	(0%)	(51%)	(48%)

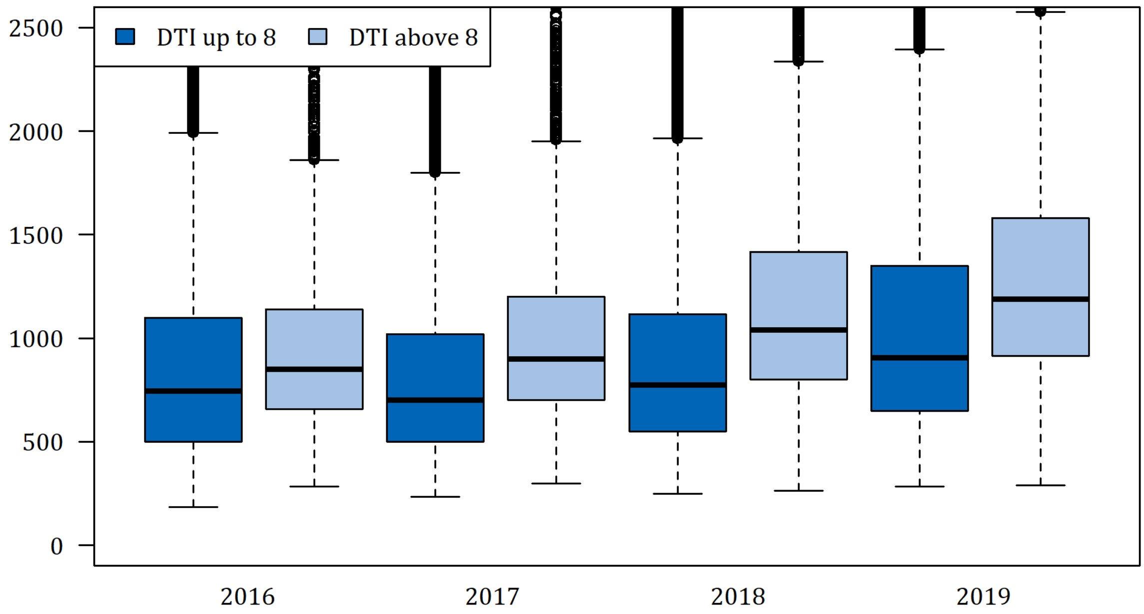
Source: NBS.

Table 4 Distribution of newly granted loans based on DTI and education - debtors with at least one housing loan

	Highest education of borrowers			
	Number (share)	At most primary	At most secondary	Tertiary
2016 up to 8	24 727	999	15 949	7 779
	(88%)	(4%)	(65%)	(31%)
2016 above 8	3 292	9	2 057	1 226
	(12%)	(0%)	(62%)	(37%)
2017 up to 8	26 532	139	17 368	9 025
	(86%)	(1%)	(65%)	(34%)
2017 above 8	4 214	5	2 718	1 491
	(14%)	(0%)	(64%)	(35%)
2018 up to 8	48 729	166	28 899	19 664
	(88%)	(0%)	(59%)	(40%)
2018 above 8	6 465	9	3 556	2 900
	(12%)	(0%)	(55%)	(45%)
2019 up to 8	76 898	368	43 104	33 426
	(95%)	(0%)	(56%)	(43%)
2019 above 8	3 746	3	1 581	2 162
	(5%)	(0%)	(42%)	(58%)

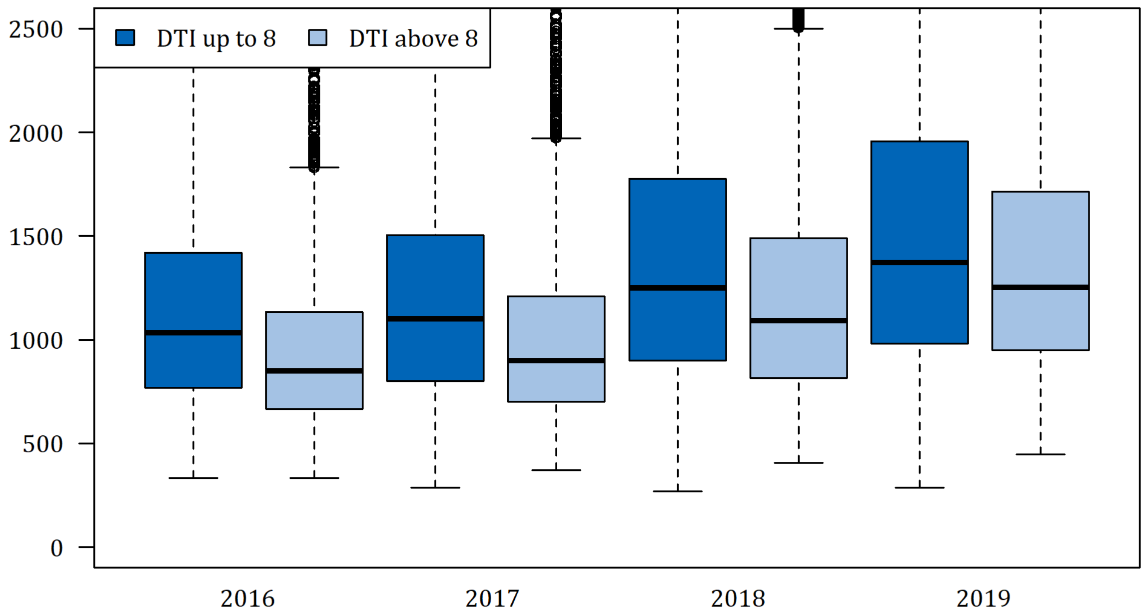
Source: NBS.

Chart 5 Distribution of newly granted loans based on DTI and income – all debtors



Source: NBS.
Note: Income in EUR is shown in the y-axes.

Chart 6 Distribution of newly granted loans based on DTI and income – debtors with at least one housing loan



Source: NBS.
Note: Income in EUR is shown in the y-axes.

4.3. LTV limit

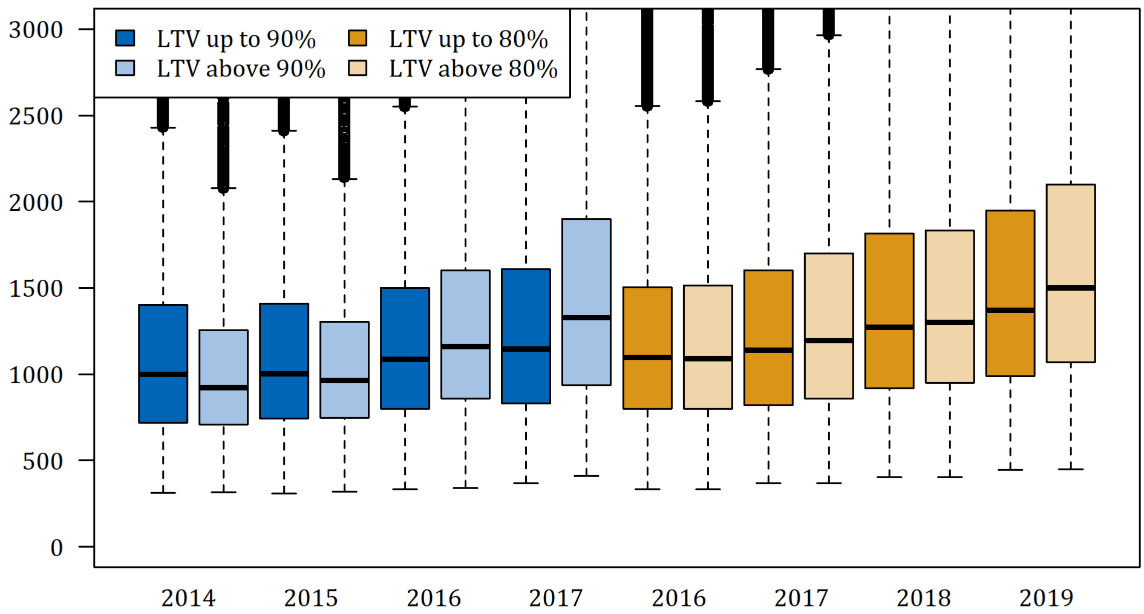
The LTV limit has been gradually tightened since end-2014. First a limit of 100% was introduced with a gradual tightening of the share of loans with LTV between 90% and 100%. Then, since July 2018, the maximum limit has been lowered to 90% with a gradual tightening of the share of loans with LTV between 80% and 90%. LTV tightening was significant also in terms of potentially affected clients. In 2014, before the 100% LTV was introduced, more than

20% of debtors got a loan with LTV exceeding this limit. In 2017, before tightening to 90%, more than 30% of debtors had a loan with LTV exceeding this limit.

The share of debtors with tertiary education and LTV above the respective limits is somewhat higher than the share of such debtors under the LTV limits (Table 5), while the share above limits is increasing with the tightening of these limits. Income distribution changed over time. In 2014 – 2015 borrowers under the LTV limits had higher average income, since 2016 this has changed (Chart 7). During the whole period there is a significant difference between the age of borrowers under and above the limits. Borrowers with LTV above the limits are in general younger at the time of the origination of the loan (Chart 8).

The implementation of LTV limits has changed the distribution of newly granted loans as well (Appendix 8). First, the distribution is switching to the left, with an increasing concentration at the limits. Second, while there was a higher concentration of loans granted around several values of LTV up to 50%, this has gradually diminished. The increasing concentration of borrowers just under the limits points to the fact that some of the affected borrowers took out a loan even after the imposition of limits, just with a lower than planned LTV. The decreasing number of peaks in the distribution at lower LTV values could point to the fact that the implementation of limits affected internal management in the banks as well, moving borrowers to the limits not just from the "right", but also from the "left".

Chart 7 Distribution of newly granted loans based on LTV and income



Source: NBS.
Note: Income in EUR is shown in the y-axes.

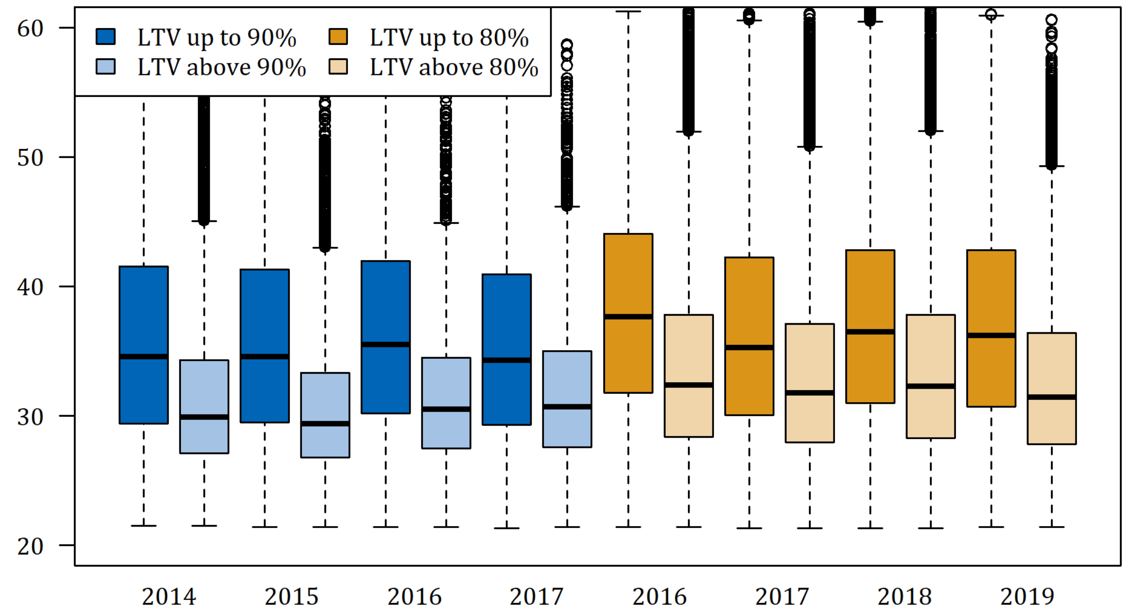
Econometric analysis confirms the importance of age (Appendix 9). Borrowers with tertiary education had a lower probability of asking for a loan exceeding 80% LTV, while in the case of 90% LTV there was no significant difference between borrowers with secondary or tertiary education. This has changed with the tightening of limits and exceptions. The probability that a loan with higher LTV will be granted to borrowers with higher education increased over time. The impact of income has changed over time as well. Since 2019, borrowers with higher income have a higher probability of getting a loan with LTV within the exceptions. The number of borrowers is an important explanatory factor in years 2016 – 2019, when loans granted to more borrowers (co-debtors) had a higher probability of having LTV below limits.

Table 5 Distribution of newly granted loans based on LTV and education

	Highest education of borrowers			
	Number (share)	At most primary	At most secondary	Tertiary
2014 up to 90	27 700 (78 %)	1 920 (7 %)	16 385 (59 %)	9 395 (34 %)
2014 above 90	7 767 (22 %)	146 (2 %)	4 499 (58 %)	3 122 (40 %)
2015 up to 90	33 487 (87 %)	1 033 (3 %)	19 637 (59 %)	12 817 (38 %)
2015 above 90	5 184 (13 %)	46 (1 %)	2 874 (55 %)	2 264 (44 %)
2016 up to 90	65 146 (94 %)	1 183 (2 %)	37 715 (58 %)	26 248 (40 %)
2016 above 90	3 895 (6 %)	81 (2 %)	1 541 (40 %)	2 273 (58 %)
2017 up to 90	84 530 (96 %)	303 (0 %)	46 160 (55 %)	38 067 (45 %)
2017 above 90	3 945 (4 %)	2 (0 %)	1 599 (41 %)	2 344 (59 %)
2016 up to 80	39 864 (58 %)	840 (2 %)	23 709 (59 %)	15 315 (38 %)
2016 above 80	29 177 (42 %)	424 (1 %)	15 547 (53 %)	13 206 (45 %)
2017 up to 80	60 752 (69 %)	243 (0 %)	34 179 (56 %)	26 330 (43 %)
2017 above 80	27 723 (31 %)	62 (0 %)	13 580 (49 %)	14 081 (51 %)
2018 up to 80	62 472 (74 %)	191 (0 %)	34 933 (56 %)	27 348 (44 %)
2018 above 80	22 433 (26 %)	72 (0 %)	11 885 (53 %)	10 476 (47 %)
2019 up to 80	73 327 (87 %)	299 (0 %)	40 797 (56 %)	32 231 (44 %)
2019 above 80	11 363 (13 %)	13 (0 %)	5 581 (49 %)	5 769 (51 %)

Source: NBS.

Chart 8 Distribution of newly granted loans based on LTV and age

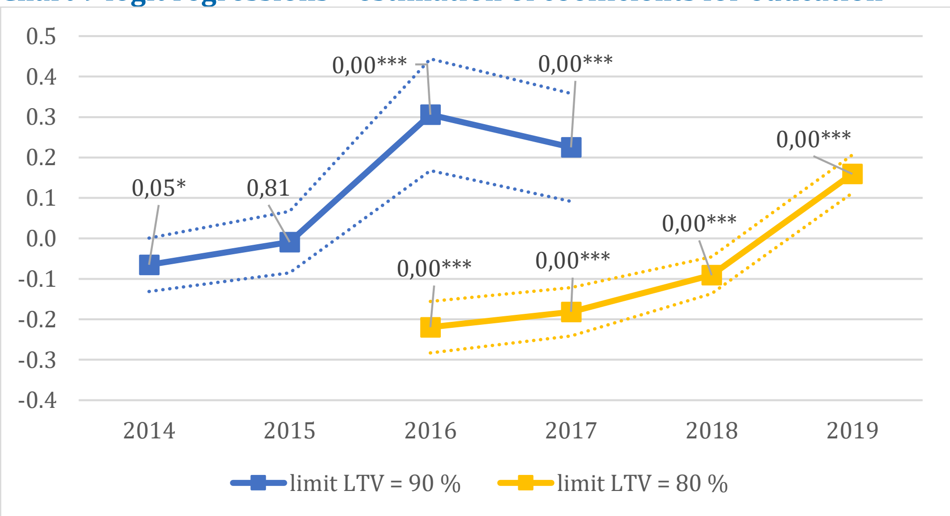


Source: NBS.
Note: Age is shown in the y-axes.

Decision trees point to the age of borrowers as a significant factor (Appendix 10). Based on the results, it is usually younger borrowers up to the age of 35 that ask for loans with an LTV exceeding consequent limits. This is in line also with the statistics presented in this part as well as with the logit regression results. This result could point to the fact that loans with higher LTV are asked for mainly by first-time homebuyers, who are in general younger.

As described above, just as in the case of DTI limits, LTV limits also have some exceptions. We can conclude from the distributions that these exceptions are granted to the above identified group of borrowers: younger debtors with higher education (Chart 9) and higher income. The tighter the limits and exceptions, the more this conclusion holds.

Chart 9 logit regressions – estimation of coefficients for education



Source: NBS.
Note: p-value is shown for each coefficient in the chart. Dotted lines represent 95% confidence intervals.
Elasticities are shown on y-axes.
* p < 0,10; ** p < 0,05; *** p < 0,01.

Evidently different limits affect different types of borrowers. DSTI limits are binding mainly for borrowers with lower education and income. DTI limits affect more borrowers asking for larger loans and LTV limits are impacting mainly younger borrowers. On the other hand, based on the change in distributions, most of the potential borrowers affected by the imposed limits finally decided to ask for a loan, adjusted to the limits in place.

5. Impact of the limits on the supply of loans

5.1. Impact of the limits on the maximum potential volume of loans

An interesting question is how binding are limits on the supply side. It is not known how many loans banks would have granted since the implementation of limits if the demand had not been affected by these limits. Loans granted during this period can, however, serve to some extent to study the supply side. We calculate for each debtor to whom a loan was granted during the following period the maximum volume of loan the bank would have been able to grant. As for the total volume of loans, as well as for the overall indebtedness, housing loans are the most important; in this section we are focusing on clients receiving a housing loan (also, based on the previous section, it is the DSTI limit binding the most for borrowers without housing loans).

We calculate the maximum attainable amount of the loan considering LTV, DTI and DSTI limits based on Kelly et al. (2015). The maximum attainable amount of loan considering a given DTI limit is:

$$Loan_{DTI} = Income * Limit_{DTI}$$

The maximum attainable amount of loan considering a given DSTI limit is:

$$Loan_{DSTI} = Income * Limit_{DSTI} \frac{1-(1+r)^{-Maturity}}{r}$$

where the maturity is calculated as the difference between the age of the borrower and the maximum age at maturity. The maximum age at maturity is defined here as the 98th percentile of the age at maturity of all loans granted at the given quarter. Calculations account for the 2 p.p. interest rate shock as well.

The maximum attainable amount of loan considering a given LTV limit is:

$$Loan_{LTV} = \frac{Financial\ assets}{100 - Limit_{LTV}} - Financial\ assets$$

As LTV is defined only for housing loans, the borrower can ask for a consumer loan to top up within the given DSTI limit[6].

$$Loan_{LTV,Top-up} = Loan_{LTV} + Consumer\ loan_{DSTI\ limit}$$

Consequently, the maximum attainable amount of the loan is calculated as:

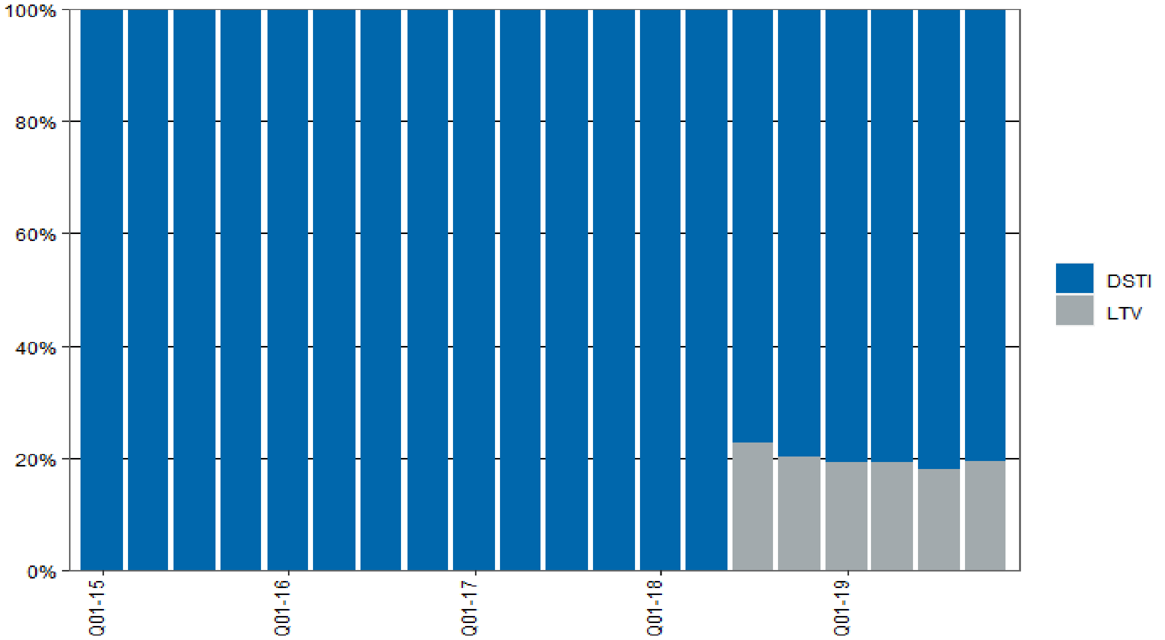
$$Loan_{Supply} = min\left(Loan_{LTV,Top-up}, Loan_{DTI}, Loan_{DSTI}\right)$$

LTV limit at the level of 100% does not constrain borrowers and is neglected, therefore. In case the LTV limit is lower than 100% and the borrower can top up the housing loan with a consumer loan up to 100% LTV (i.e. 100% of the borrower's financial assets), we assume the borrower is constrained by the DSTI rather than the LTV limit.

[6] DTI limit applies as well. However, calculating the maximum value of the loan within the given DTI limit results in $Loan_{DTI}$, this constraint is therefore not reflected.

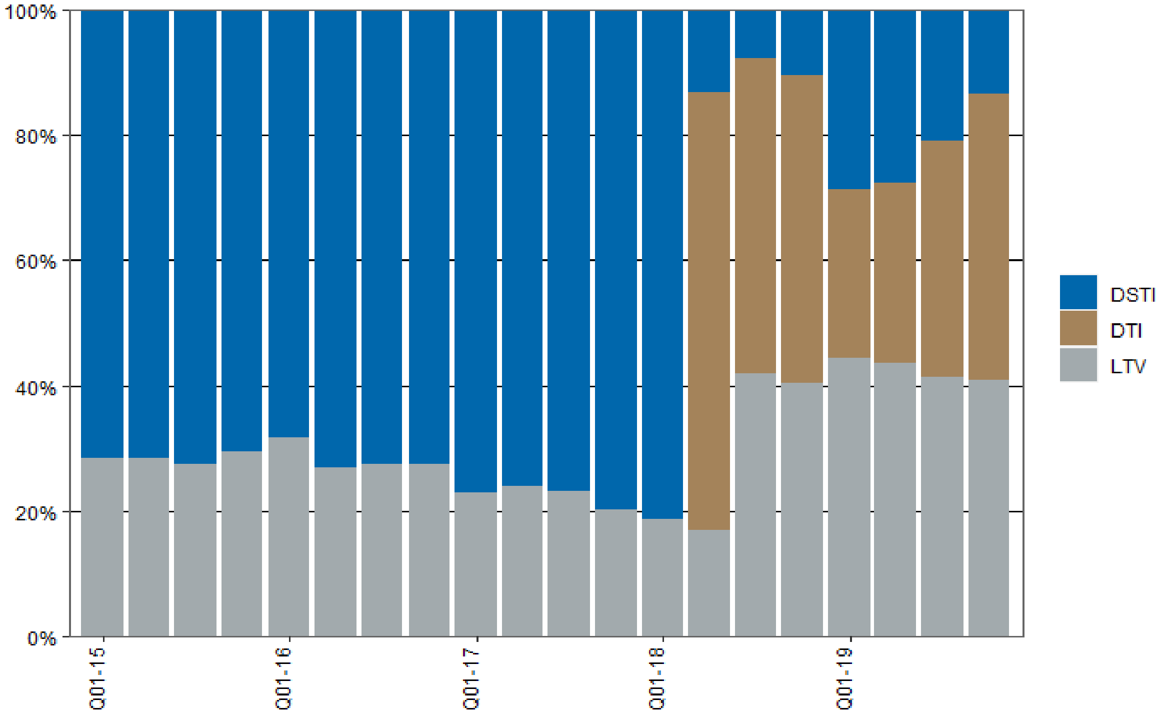
Limits were imposed with exceptions, having also potentially their upper bound. If we estimate the impact of limits for borrowers potentially qualifying for the exceptions, we are interested in the upper limits of these exceptions. In this case, LTV is not constraining until the second half of 2018, when the limit was lowered to 90% (Chart 10). Even though the LTV limit starts to be constraining after this tightening, it is the DSTI limit that is constraining the most during the entire period.

Chart 10 Constraints of respective limits – share on housing loans granted in respective quarters, upper bound of limits



Source: NBS.

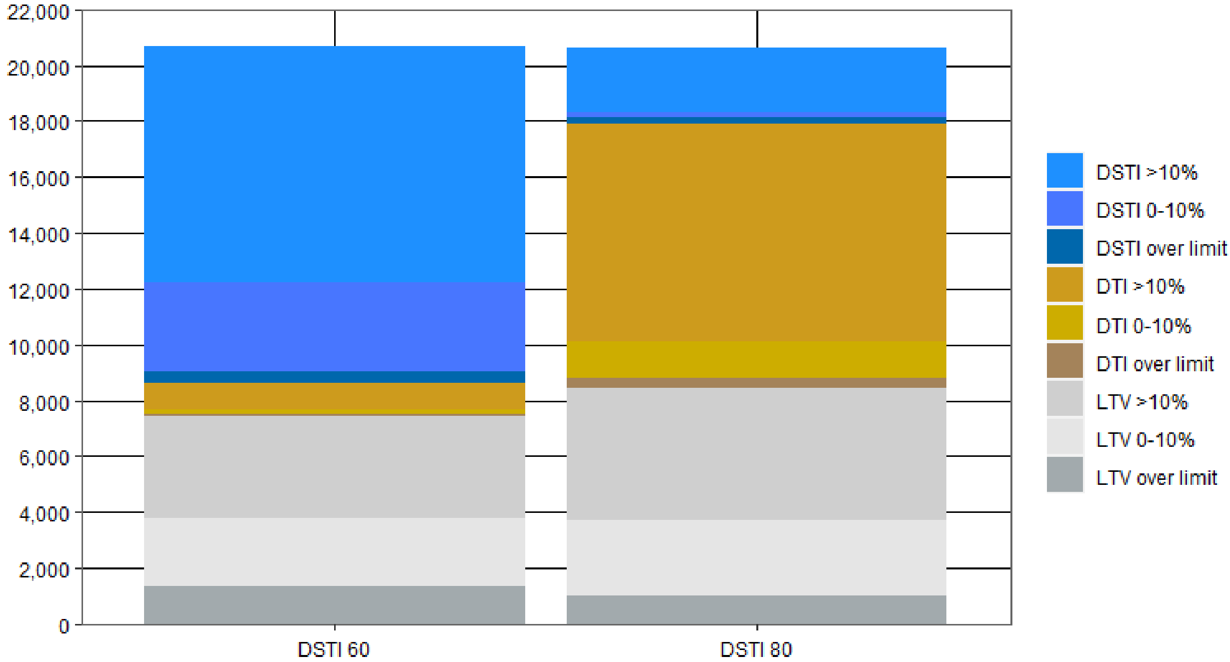
Chart 11 Constraints of respective limits – share on housing loans granted in respective quarters, lower bound of limits



Source: NBS.

However, most of the borrowers do not qualify for the exceptions. For these clients the lower bound of limits apply. In this case LTV is constraining from the beginning and DTI since 2018, however (Chart 11). After the tightening of LTV limit the share of loans, where the most constraining is the LTV or DTI limit increased significantly. However, data used end in 2019, i.e. before the DSTI limit was tightened from 80% to 60%. If the DSTI limit had been 60% in the last quarter of 2019, the share of loans constrained by this limit would have been much higher (Chart 12). On the other hand, as shown by the chart, most debtors were granted a loan below its theoretical value by more than 10% (category >10%).

Chart 12 Constraints of respective limits at 60% DSTI limit



Source: NBS.
Notes: right-hand bar shows the impact of limits as of 2019Q4. The left-hand bar shows the theoretical impact of limits at 60% DSTI.
Loans constrained by the respective limits are differentiated based on the difference between the granted loan and the theoretical maximum value of the loan. I.e., if the volume of the respective loan is lower than the theoretical volume by at most 10% (0-10%), more than 10% (>10%) or is exceeding the theoretical volume (over limit). The later one is usually because the loan was granted within the existing exceptions.
On the left-hand bar, the category DSTI 0-10% includes also loans with DSTI between 60% and 80%, as we assume in case of a tighter DSTI limits these borrowers would ask a loan exactly at the limit, i.e. at 60% DSTI.

5.2. Changes in supply after the implementation of BBMs

Measures introduced have an impact on supply as well, even though the banks could have reacted by changes in the supply of housing loans. One way to assess changes in the supply is provided by the method of stochastic frontier. Using this method, it is possible to estimate the maximum amount of loan banks may grant based on the assumed input parameters at the time of loan origination (income, own capital, age of borrowers, interest rate, collateral used). Not all the loans are granted at the maximum possible amount due to differences across regions, banks and demand, while this method enables us to estimate this "inefficiency". The assessment in this part focuses on housing loans.

The general form of the model is the following:

$$y_i = \alpha + X_i'\beta + \varepsilon_i,$$
$$\varepsilon_i = v_i - u_i,$$
$$v_i \sim N(0, \sigma_v^2),$$
$$u_i \sim F$$

where y_i is the output (loan), X_i is a vector of inputs (all variables are used in log form), α and β are coefficients estimated, ε_i are residuals consisting of a two-sided normally distributed noise component, v_i, and a non-negative technical inefficiency component, u_i. A similar approach is used by Kelly and Mazza (2019) or Anenberg et al. (2019). A detailed description of this approach is in Belotti et al. (2013).

Table 6 Stochastic frontier parameter estimations

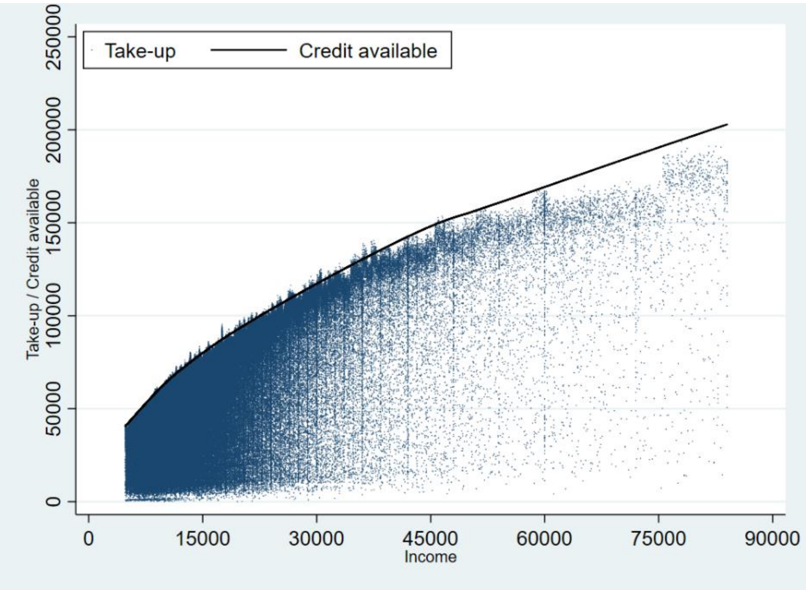
Production function (log(loan))	Model 1	Model 2
Log(income)	0.61***	0.05***
Log(own capital)	0.08***	-0.09***
Log(age)	-0.48***	-0.09***
Log(interest rate)	-0.15***	0.02***
Log(collateral)		1.04***
Intercept	5.62***	0.22***
u_i		
Log(income)	-0.83***	-2.27***
Log(own capital)	0.43***	5.44***
Log(age)	1.82***	0.42***
Log(interest rate)	1.02***	0.68***
Log(collateral)		-3.51***

Source: NBS.
Notes: * p < 0,10; ** p < 0,05; *** p < 0,01.
Differences across regions and banks are considered.

We estimate both the amount of loan (production function) and the inefficiency term, u_i. Income, the borrower's own capital, age and interest rates have been chosen as explanatory variables. We estimate two specifications, one excluding and one including the value of underlying collateral. We also control for regions and banks. Estimated results for the whole period are summarised in Table 6. Under both specifications, there is a positive impact of income on the production function. Increasing age decreases the maximum credit available. If collateral is excluded, the coefficient estimated for own capital is positive and the coefficient estimated for interest rate is negative. If the collateral is included, the estimated coefficient is positive and close to 1. On the other hand, the coefficient for own capital changes to negative and for interest rates to positive. Under this second specification, the maximum amount of loan, or credit available, is estimated practically as the value of collateral minus own funds. If there are two loans with the same value of collateral, the larger loan having higher LTV is estimated to be more expensive, which is expressed by the positive coefficient for the interest rate. Including the collateral decreases significantly differences across regions and banks.

Based on the estimated coefficients, the inefficiency term, u_i, is decreasing by increasing income and collateral and increasing by increasing own capital. The dependence of the maximum credit available on income is shown by Chart 13.

Chart 13 Maximum credit available base on income

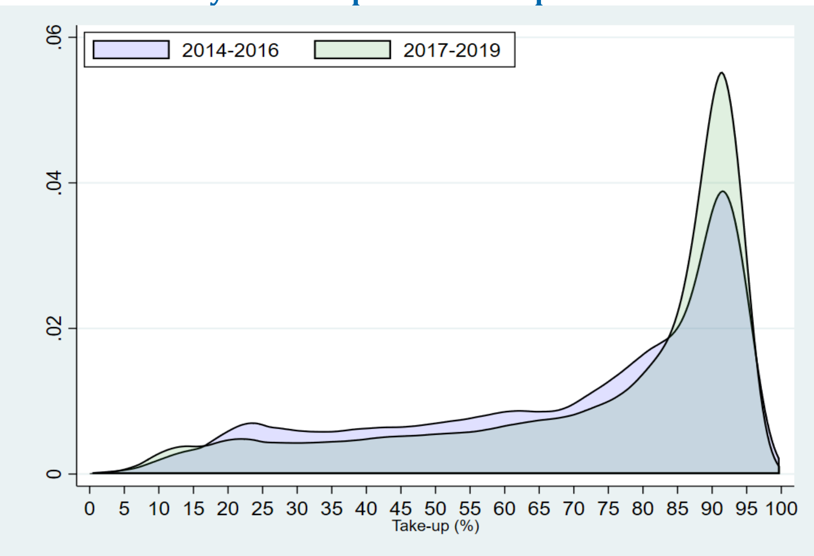


Source: NBS.
note: Maximum credit available is estimated within income brackets. Some granted loans are above the estimated upper boundary due to the way this boundary is smoothed across different income brackets.

Estimations by years allow us to follow the change of the share of the amount of loans granted of their theoretical maximum value (the credit available), it means to follow changes in the so-called take-up.

As is shown by Chart 14, the take-up increased in the period 2017 – 2019 (when most of the limits were already in place), compared to 2014 – 2016, when most of the limits started to be implemented[7]. It means that loans were granted closer to their theoretical maximum amount. This could be a consequence of the impact of BBMs on the maximum credit available and also the reaction of banks allowing for some clients to draw a higher amount of loan compared to the period with no BBMs.

Chart 14 Density of take-up in different periods



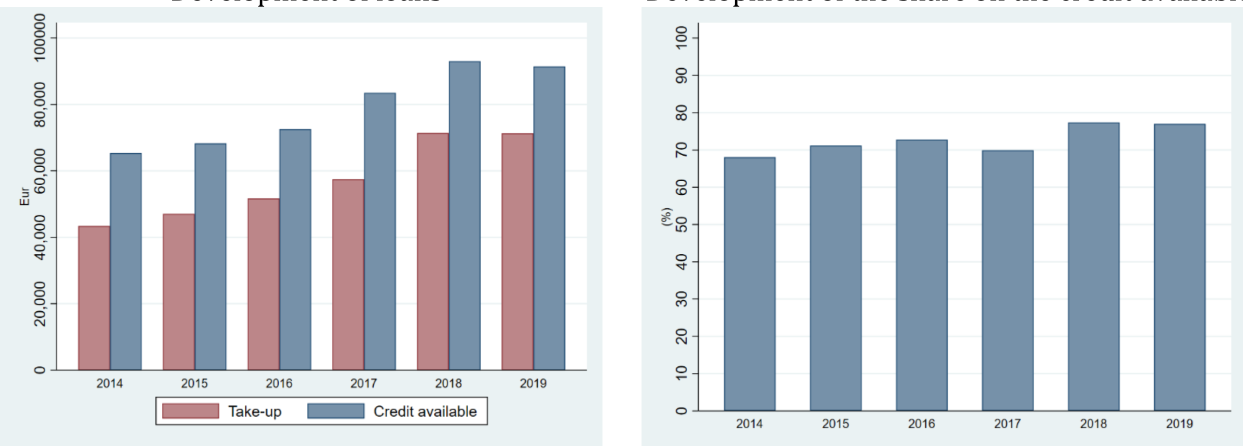
Source: NBS.

[7] Even if such a division of the whole period is not completely exact, it is chosen to make the graphical presentation easier.

Estimation of the average take-up and credit available on a yearly basis points to increasing take-up (Chart 15). In 2014, loans on average were granted at 70% of the estimated credit available. In 2018 and 2019, this take-up increased to almost 80%. Credit available gradually increased, while in 2019 it remained at the same level as in 2018. This could be a consequence of the impact of measures implemented on the maximum available amount of loans.

Chart 15 Yearly credit development

Development of loans | Development of the share on the credit available



Source: NBS.

6. Impact of the limits on the volume of loans

6.1. DSTI limit

The introduction of BBMs has a direct impact on potential borrowers planning to ask for a loan exceeding these limits. As after the measures are implemented no such loans (exceeding the limits) are provided (only within allowed exceptions), we can only estimate the theoretical volume/share of such loans. For the estimated impact, we use loan distributions before the implementation of measures. In the case of DSTI, the limit of 100% and consequently the limit of 80% was introduced in the period under consideration, with a gradual phase-in. In the case of households potentially asking for loans exceeding the consequent limits, we assume they refuse to ask for a loan or ask for a loan with parameters as close to the planned loan as possible, i.e. with parameters close to the limits. It means that the share of loans with DSTI above 100% or above 80% of the total volume of loans could be an incorrect measure, as part of the distribution above these limits could shift under these limits. Therefore, in the table below and analysis we work with the share of loans with DSTI above 100% or 80% in respective years of the volume of loans with DSTI up to 50%.[8]

The share of loans with DSTI exceeding 100% was low even in 2014 (Table 7). Therefore, we focus on the limit of 80% entering into force in July 2018, after a gradual phase-in since the beginning of 2017. The share of housing loans with DSTI above 80% was in 2015, before the gradual phase-in and before the introduction of the new legislation related to the conditions of refinancing, 26% of the volume of loans with DSTI up to 50%. This share was 24% in the case of consumer loans. In 2017 and 2018 this share in the case of consumer loans gradually decreased. In 2019, after the full phase-in, this share was positive only because of exceptions. This share in the case of housing loans, on the other hand, increased slightly in 2017, pointing to possible front-loading during the phase-in period.

[8] The share of the volume of loans with DSTI up to 50% was chosen to minimalize the probability that potential borrowers originally planning to ask for a loan exceeding the consequent limits will ask for a loan belonging to this category.

Table 7 Distribution of newly granted loans based on DSTI

Housing loans	Share of loans with DSTI above 80% of the volume of loans with DSTI up to 50%	Share of loans with DSTI above 100% of the volume of loans with DSTI up to 50%
2014	8.4%	0.0%
2015	26.1%	0.0%
2016	27.8%	0.0%
2017	30.8%	0.0%
2018	17.8%	0.0%
2019	0.8%	0.0%
Consumer loans		
2014	14.7%	0.5%
2015	23.6%	1.3%
2016	16.3%	1.6%
2017	12.4%	0.7%
2018	13.2%	1.9%
2019	2.2%	0.0%

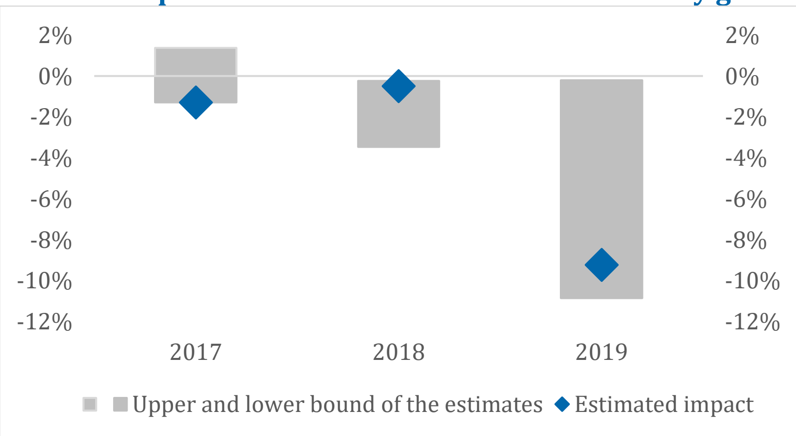
Source: NBS.

An assumption necessary for the estimation of the impact of the DSTI limit is that without this measure, the distribution of loans would have remained equal to the distribution in 2015. It means the share of housing loans exceeding DSTI 80% would be around 26% and that of consumer loans would be 24% of the volume of loans having DSTI up to 50%. To reach an upper and lower bound of the theoretical impact of the DSTI limit we assume:[9]

- all households originally planning to ask for a loan with a DSTI above 80% asked for a loan with DSTI exactly 80%;
- none of the households originally planning to ask for a loan with a DSTI above 80% asked for a loan.

Based on this upper and lower bound, the overall volume of newly granted loans possibly decreased in 2019 compared to their theoretical values without DSTI measures by almost 11%.

Chart 16 Impact of DSTI limit on the volume of newly granted loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

[9] When estimating the impact of limits on the volume of loans, the possible decrease of the volume due to the decrease of average DSTI in a given category is taken into account. If the average DSTI of loans with DSTI above 80% in a given year is lower than the average DSTI of loans with DSTI above 80% in 2015, the volume of loans above this 80% DSTI is lower compared to 2015.

Table 8 Share of loans with DSTI between 70% and 80%

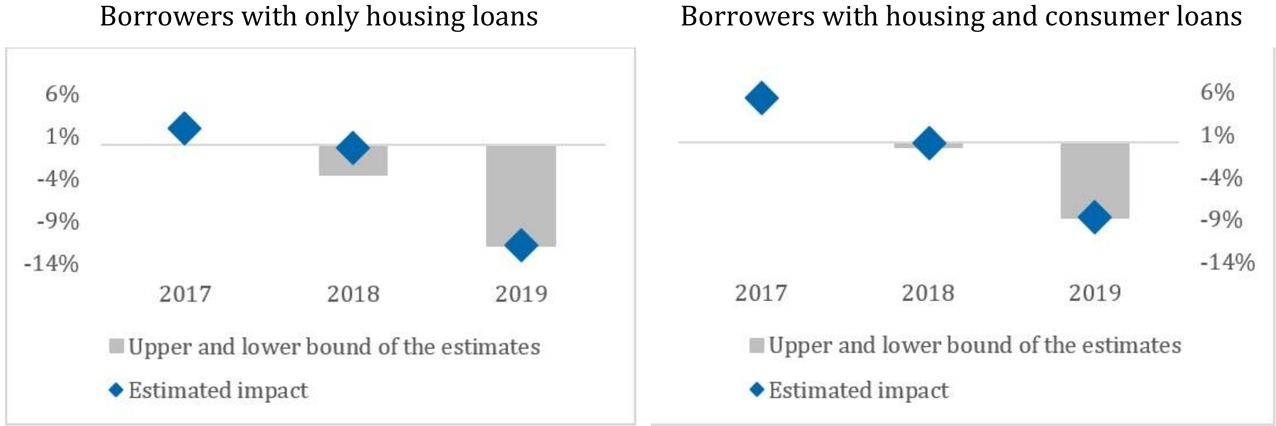
Housing loans	Share of loans with DSTI between 70% and 80% of the volume of loans with DSTI up to 50%
2014	11.5%
2015	25.6%
2016	28.4%
2017	32.6%
2018	39.4%
2019	21.5%
Consumer loans	
2014	12.9%
2015	17.5%
2016	12.5%
2017	10.1%
2018	27.0%
2019	39.3%

Source: NBS.

On the other hand, if some of the borrowers potentially asking for a loan exceeding consecutive DSTI limits take a loan just under the limit, the share of loans with DSTI just under the limit increases. In this case it means that the share of loans with DSTI between 70% and 80% of the volume of loans with DSTI up to 50% increases. In the case of housing loans, this share increased from 25% in 2015 to 39% in 2018 (Table 8). As the share of loans with DSTI above 80% decreased by less (more than 8 p.p.) than the increase of the share of loans with DSTI between 70% and 80% (14 p.p.), we assume all clients potentially asking for a loan above the limit finally took a loan. In the case of consumer loans, the share of loans with DSTI between 70% and 80% in the same period increased by 9.5 p.p. and the share of loans with DSTI above 80% decreased by 10.4 p.p. Therefore, we assume not all the debtors potentially asking for a consumer loan exceeding 80% DSTI asked for a consumer loan with lower DSTI (we assume 9.5/10.4, i.e. around 92% of such potential borrowers finally asked for a consumer loan). Chart 16 shows the upper and lower bound of the possible impact of the DSTI limit as well as the estimated impact. In 2017 and 2018 the estimated impact was milder than in 2019. This result confirms the possible front-loading before 2019 due to the gradual phase-in of the DSTI limit.

We also looked at the impact of the limit on borrowers asking only for housing loans and on borrowers asking for both housing and consumer loans. The time-dimension of the impact is similar, but the amplitude of the impact is lower in case of borrowers asking for both types of loans (Chart 17). This probably reflects that borrowers asking also for a consumer loan can in the case of tighter limits lower the volume of consumer loan and thus the impact on the volume of housing loan is lower.

Chart 17 Impact of DSTI limit on the volume of newly granted housing loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

6.2. DTI limit

Table 9 Distribution of newly granted loans based on DTI

Housing loans	Share of loans with DTI above 8 of the volume of loans with DTI up to 5
2014	23.5%
2015	30.2%
2016	40.0%
2017	50.8%
2018	41.4%
2019	15.6%
Consumer loans	
2014	0.7%
2015	0.8%
2016	0.9%
2017	1.4%
2018	1.9%
2019	1.3%

Source: NBS.
Note: Share of the volume of loans.

The DTI limit of 8 was implemented in 2018 with a gradual phase-in until July 2019. Until 2017, the last year before the implementation, the share of, mainly, housing loans with DTI above 8 of the volume of housing loans with DTI up to 5, increased[10]. After the introduction of the limit this share decreased from 51 % to 16 %. Consumer loans were not affected to a large extent by this limit, reflected also in the small share of such loans exceeding DTI of 8.

Again, Table 9 shows data used to estimate the upper and lower bound of the impact of DTI limit. To estimate the possible impact, we also use the change in the share of loans with DTI between 7 and 8 of the volume of loans with DTI up to 5 (Table 10), as some borrowers potentially asking for a loan with DTI exceeding 8 could ask for a loan with DTI between 7 and 8, probably just under 8. In the case of housing loans, this share increased significantly from 25.7% in 2017 to 49.2% in 2019. The estimated "real" impact at the level of 3.2% is, therefore,

[10] For DTI, similarly as for DSTI, we are interested in the change of the share of the volume of loans with DTI up to 5. Again, this is to minimalize the probability that potential borrowers originally planning to ask for a loan exceeding the consequent limits will ask for a loan belonging to this category.

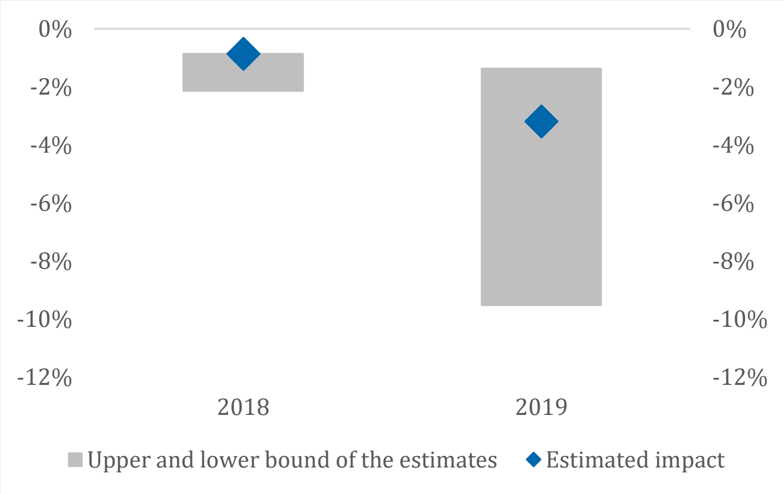
close to the lower bound of the estimates, while the overall interval of possible impact ranges from 1.4% to 9.4% (Chart 18).

Table 10 Share of loans with DTI between 7 and 8

Housing loans	Share of loans with DTI between 7 and 8 of the volume of loans with DTI up to 5
2014	13.2%
2015	18.0%
2016	19.9%
2017	25.7%
2018	35.8%
2019	49.2%
Consumer loans	
2014	0.4%
2015	0.9%
2016	1.0%
2017	1.5%
2018	2.5%
2019	4.8%

Source: NBS.
Note: Share of the volume of loans.

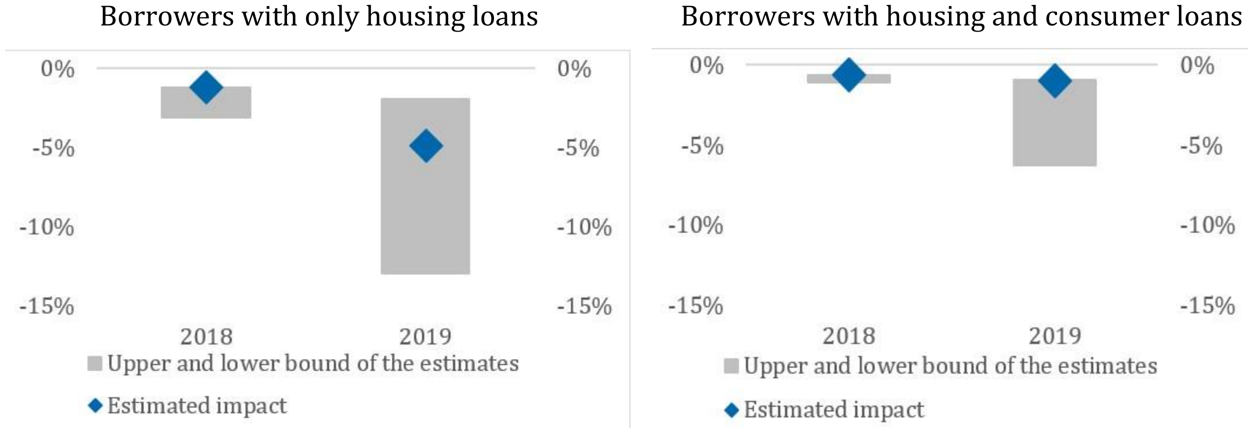
Chart 18 Impact of DTI limit on the volume of newly granted loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

Again, the impact is higher for borrowers asking only for a housing loan than for borrowers asking for both housing and consumer loan (Chart 19). This can again reflect the fact that borrowers asking for both loans could transmit the tighter limits to lower volume of consumer loans and thus the volume of housing loans was affected to a lesser extent.

Chart 19 Impact of DTI limit on the volume of newly granted housing loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

6.3. LTV limit

Table 11 Share of newly granted loans with LTV above 80% and 90%

	Share of loans with LTV above 80% of the volume of loans with LTV up to 60%	Share of loans with LTV above 90% of the volume of loans with LTV up to 60%
2014	192.8%	111.7%
2015	179.4%	69.7%
2016	124.5%	16.0%
2017	143.7%	22.2%
2018	159.0%	14.4%
2019	86.4%	0.0%

Source: NBS.
Note: Share of the volume of housing loans.

The gradual tightening of LTV limits can be divided into two parts. During the first phase, from end-2014 to the first half of 2017, the limit of 100% LTV was introduced with a gradual tightening of the share of loans with LTV above 90%. During the second phase, from July 2018 to July 2019, the limit of 90% LTV was introduced with a gradual tightening of the share of loans with LTV above 80%. Due to the gradual tightening, the share of loans with LTV above 80% and 90% of the volume of loans with LTV up to 60% decreased significantly (Table 11).

Table 12 Share of newly granted loans with LTV between 70% and 80%

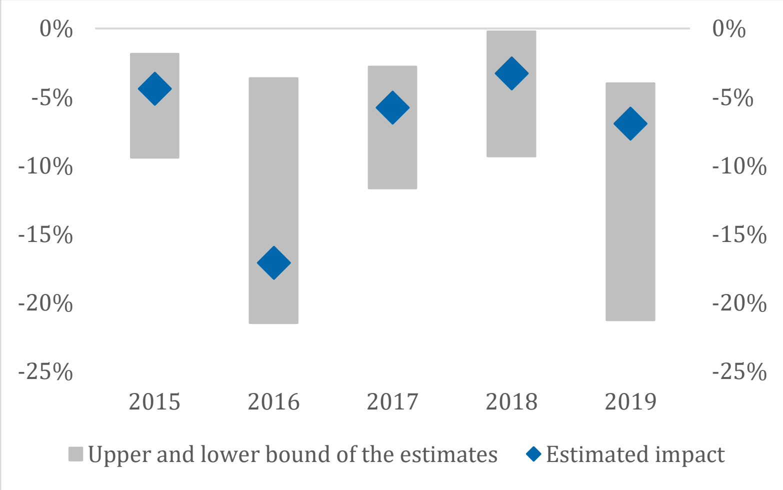
	Share of loans with LTV between 70% an 80% of the volume of loans with LTV up to 60%
2014	66.8%
2015	68.0%
2016	54.0%
2017	100.4%
2018	171.4%
2019	229.1%

Source: NBS.
Note: Share of the volume of housing loans.

On the other hand, the distribution of loans based on LTV changed the most as well. It is visible also in the share of loans with LTV between 70% and 80%, i.e. in the range where potential borrowers planning to ask for loans with LTV above 80% probably took a loan finally. The share of such loans of the volume of loans with LTV up to 60% increased from 67% in 2014 to almost 230% in 2019 (Table 12).

The impact of the implemented LTV measures is mild, therefore. The highest impact is estimated in 2016, but in this year new legislation was introduced, affecting refinancing with a possible consequent impact also on the estimates for this year. In 2019, the estimated decrease of the volume of loans is -7% (Chart 20).

Chart 20 Impact of LTV limit on the volume of newly granted loans

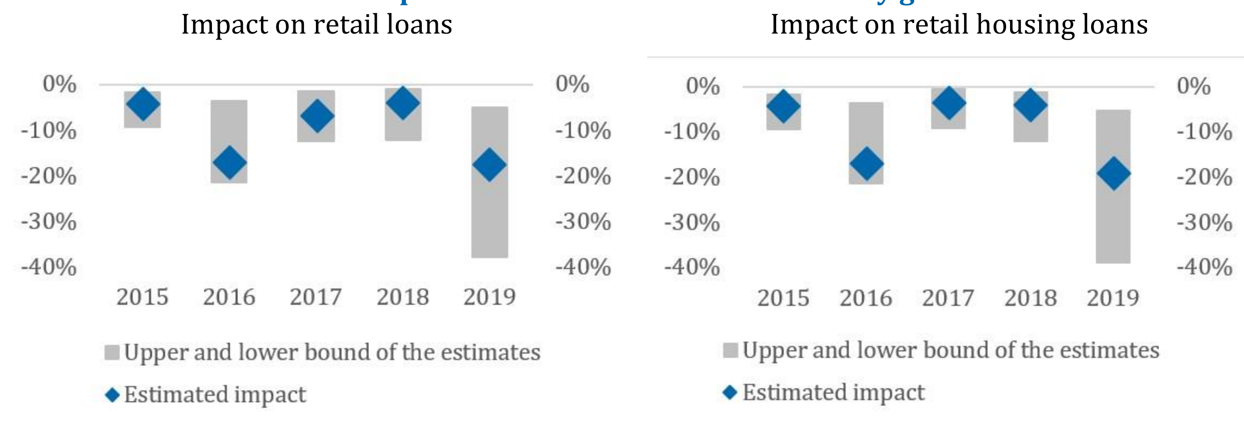


Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

6.4. Overall impact

While in 2015 and 2016 the volume of loans was affected only by the gradual tightening of LTV measures, in the consequent years other measures were gradually tightened as well. The possible overlap of respective limits is taken into account when estimating the overall impact, while only the measure with the highest impact on a given loan enters the estimations.

Chart 21 Overall estimated impact of limits on the volume of newly granted loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

The difference between the impact on overall retail loans and on retail housing loans is relatively small due to the high share of the volume of newly granted housing loans in the volume of newly granted retail loans (Chart 21). The highest impact is in 2016 (affected also by legislative changes) and in 2019, when the impact of DTI and DSTI limits was the highest. In 2019, we estimate that the volume of newly granted loans was lowered by 17% and the volume of newly granted housing loans by 19% by the measures. It means that without the measures in place, the volume of retail loans would have been higher by 17% compared to the actual figures in this year.

6.5. Reaction of banks

The introduction of BBMs might have not only a reducing impact on the loan growth in the form of moving some of borrowers planning to ask for loans potentially exceeding consequent limits under these limits, at least based on annual changes of loan distributions. It seems that some borrowers potentially asking for loans well below the limits were "pushed" closer to the limits. This can be a consequence of the banks' activity, that could have compensated for the volume of loans lost above the limits by "moving" those clients under the limits closer to these limits[11].

To estimate the impact of the measures, including the possible reaction of banks, we use the same assumption as in the previous parts, i.e. that without the measures the distributions of loans would be the same as in the reference year[12]. However, in this case we compare not only changes in the distribution of loans closely above and under the limits, but also in a wider range under the limits[13]. As previously, we compare changes in the share of loans with DSTI up to 50%, DTI up to 5 and LTV up to 60%.

The assumption that all borrowers potentially asking for a loan exceeding consequent limits decide to ask for a loan just under the limit yields an upper bound of the estimated impact. The remaining increase of share of a given range is then assumed to be caused by the activity of banks moving some borrowers up to this range. The assumption that none of the potential borrowers planning to ask for a loan exceeding consecutive limits decide to ask for a loan yields a lower bound of the estimation. At the same time, banks haven't moved any of the borrowers "up", closer to the limits. The changes in the distribution above the limits and in a wider range below the limits yields the median estimation. If part of the clients with loans above the BBM limits decides to ask for a loan and part of the potential borrowers decides not to ask for a loan, the share of loans within the following range would decrease. On the other hand, if banks "move" some borrowers from the lower end of the distributions closer to the limits, the share of the given ranges can potentially even increase, despite the decrease of the share above the imposed limit.

Based on the above methodology, banks compensated for the volume of loans lost above the DSTI limits in 2017; in 2018 the volume of loans could even increase (compared to the theoretical volume in this year without measures) by 15%. On the other hand, in 2019, after the full phase-in of the DSTI limit, the volume of loans could decrease by even 11% (Chart 22).

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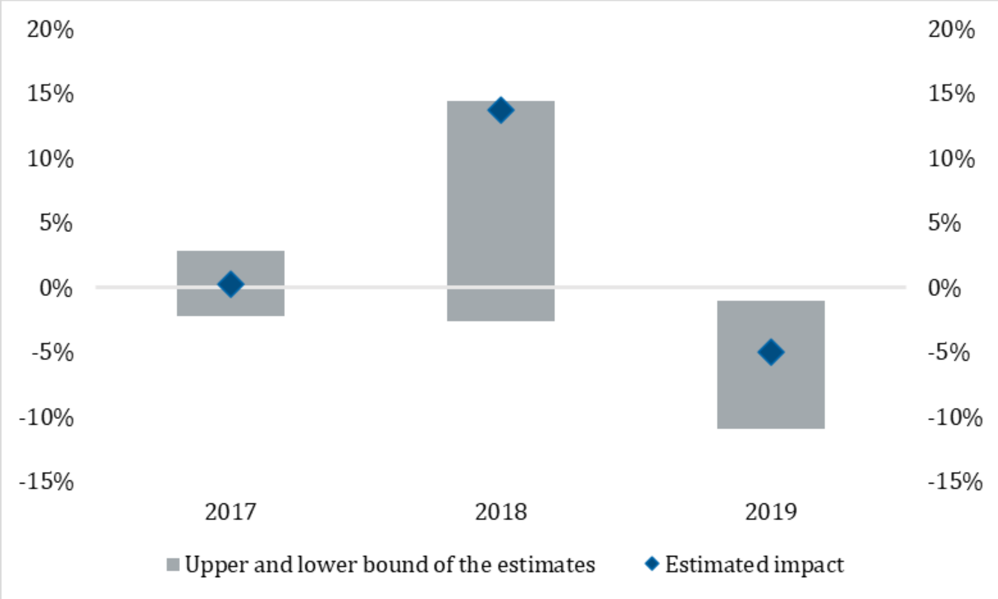
[11] In practice, banks could ease their internal risk management limits after the introduction of measures by NBS. This easing enabled the granting of loans with higher LTV, DTI or DSTI (within limits introduced by NBS) to part of the clients that could not achieve such loans based on the original internal limits.

[12] For DSTI = 80% it is year 2015, for DTI = 8 2017, for LTV = 90% 2014 and for LTV = 80% 2017.

[13] For DSTI = 80% the range is ⟨50%, 80%⟩, for DTI = 8 ⟨5,8⟩, for LTV = 90% ⟨60%, 90%⟩ and for LTV = 80% ⟨60%, 80%⟩.

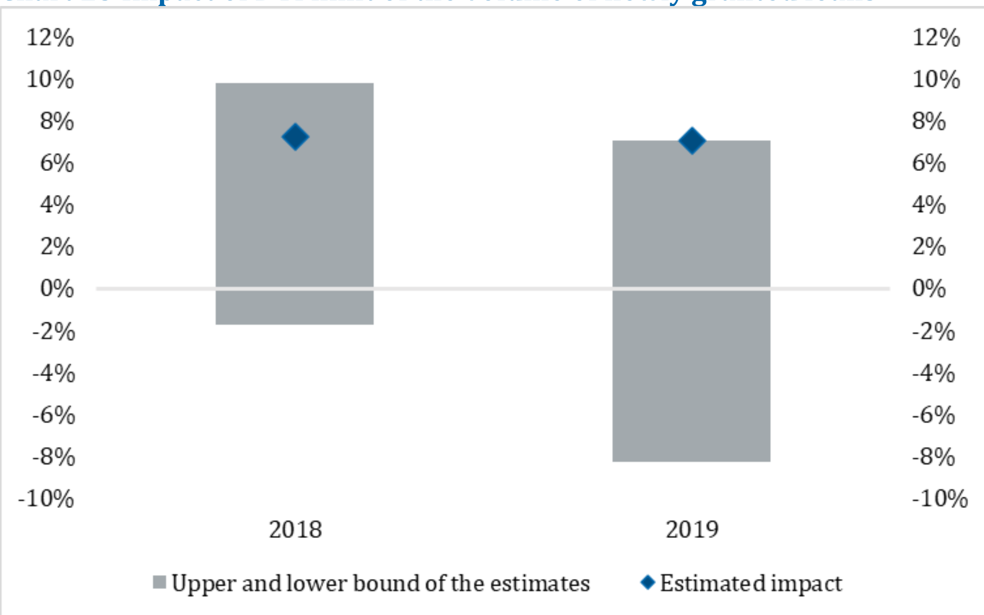
Chart 22 Impact of DSTI limit on the volume of newly granted loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

Estimations for DTI limits show a possible increase of the volume of loans in 2018 and 2019 by 7%, which is close to the upper bound of the estimates. The lower bound in both years points to a possible decrease of the volume of loans, in 2019 by 8% compared to the theoretical value (Chart 23).

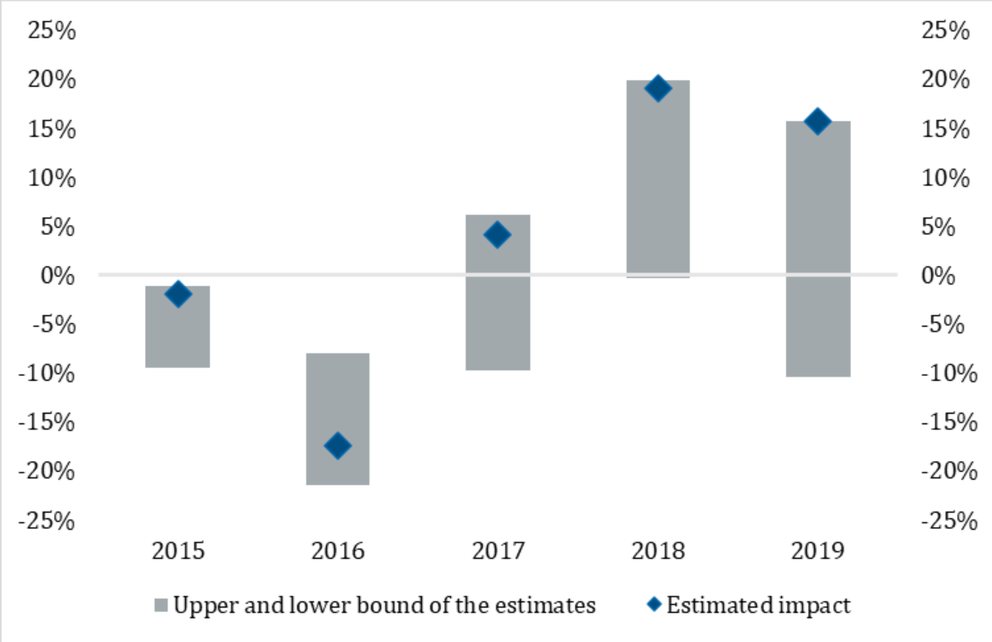
Chart 23 Impact of DTI limit of the volume of newly granted loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

Estimations for the LTV limits show that despite the effort of banks to compensate for the impact of the measures, in 2015 and 2016 the volume of loans decreased compared to their theoretical value. In the following years the "upper" bound of the estimations points to a possible increase of loans, in 2018 even by 20% compared to their theoretical value without the measures (Chart 24).

Chart 24 Impact of LTV limit on the volume of newly granted loans



Source: NBS.
Note: Chart shows percentage changes in the volume of estimated newly granted loans.

Naturally, the distribution of loans based on the respective limits is affected by multiple factors. The high pace of refinancing since 2016 or errors in the reporting can result in a large difference between the currently available distributions and the true distribution of loans in earlier years. It is necessary to take into account these drawbacks when interpreting quantitative results. On the other hand, estimations confirm at least qualitatively that while the measures imposed lowered the volume of loans, banks have been trying to compensate for this impact.

7. Impact of the limits on residential real estate prices

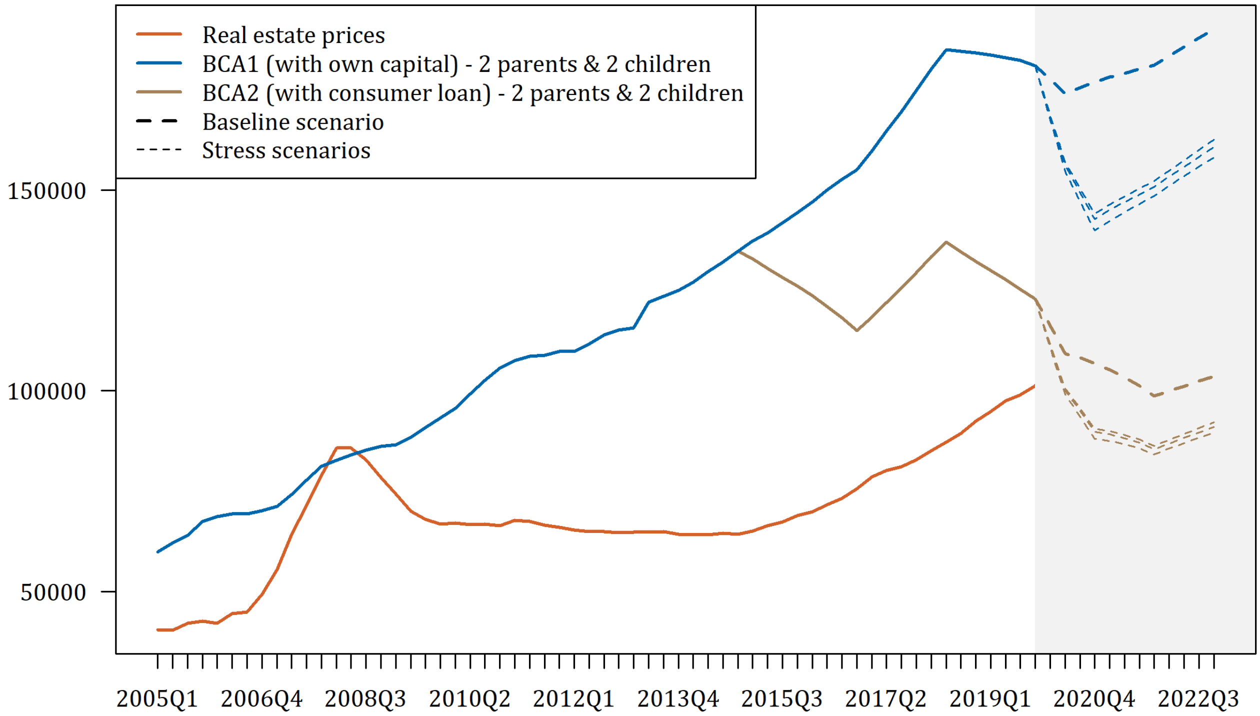
7.1. Qualitative impact

We estimate the qualitative impact of the BBMs on real estate prices using the evaluation of residential real estate prices by loan availability (Borrowing Capacity Approach, BCA). For a given household, we estimate the maximum attainable value of housing loan using similar methodology as described in Cesnak and Klacso (2021). This enables us to directly account for the impact of BBMs on the attainable amount of loan. In the case of the LTV limits, we allow for a top-up of housing loan by a consumer loan within the respective DSTI and DTI limits.

Until 2019, implemented BBMs were not constraining significantly for a household with average wage using average interest rates on housing and consumer loans, as well as average wages (Chart 25). It means that the maximum attainable loan for such a household exceeded average residential real estate prices. Gradual tightening of BBMs decreased loan availability as well. At the end of 2019, the estimated attainable amount of loan for some selected type of households, mainly for those without enough capital of their own, was the closest to average residential real estate prices within the last 10 years.

Based on the predicted development of loan availability, the impact of BBMs should increase, resulting in a significant decrease of the amount of loan attainable compared to the real estate prices. Potential borrowers without enough capital of their own can be the most affected section of potential borrowers. It means that the implementation and tightening of measures lowered loan availability and it is possible to expect further lowering to levels that can affect real estate prices as well.

Chart 25 Comparison of the development of loan availability to the average real estate prices



Source: NBS, Price map.
Note: scenarios used for the prediction are described in Appendix 11.

7.2. Qualitative impact

A direct channel of the impact of BBMs on real estate prices is via the decrease of newly granted loans. The fact that the potential borrower cannot take a loan or can take a loan lower than originally planned, creates pressure on real estate prices. Error correction models were used to quantify the impact of decreasing volume of newly granted loans on real estate prices in the form of:

$$\Delta ln(RRE)_t = \alpha(ln(RRE)_{t-1} + \beta_0 + \beta_1 ln(NGL)_{t-1} + BX_{t-1}) + short - term\ impact + \varepsilon_t ,$$

where RRE stands for residential real estate prices, NGL is the volume of newly granted housing loans and X is a vector of other macroeconomic variables that includes, depending on the model used, unemployment ratio, number of working age population, effective unemployment rate or output gap. Short-term impact includes beside the above-mentioned variables, depending on the model used, the impact of GDP and interest rates on housing loans.

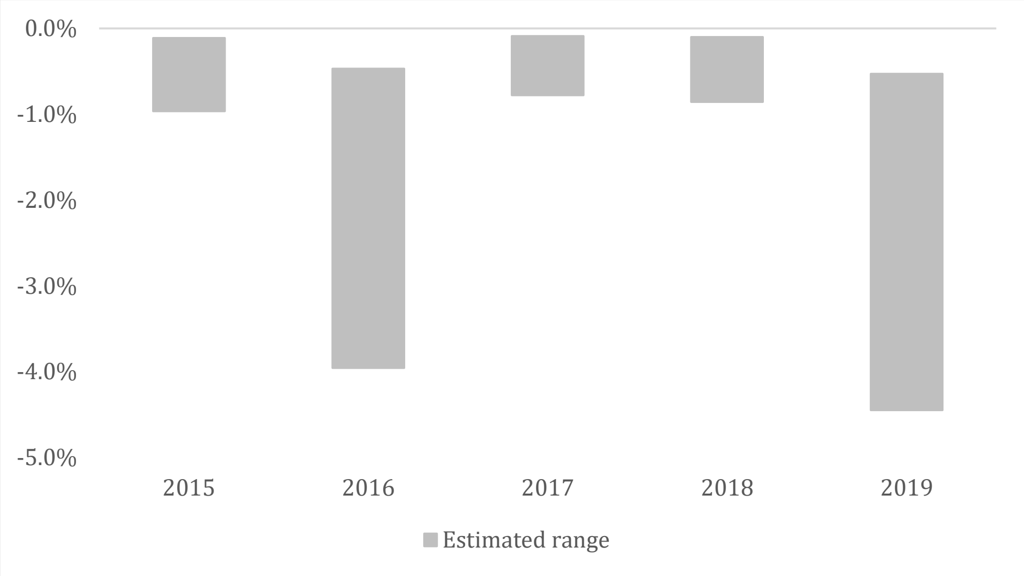
Quarterly time series are used from 2015Q1 to 2020Q1. Specifications, where cointegration of endogenous variables was not rejected and where the sign of estimated coefficients within the cointegrating equation is in line with expectations, were selected for the quantification[14]. The most important estimation results are summarized in Appendix 12.

For the long-term impact of changes in newly granted housing loans on real estate prices we are interested in the values of coefficient β_1. This coefficient expresses to what extent changes in the volume of newly granted housing loans are transmitted into changes in real estate prices in the long run. The estimated range of this coefficient is from -0.025 to -0.216. It means that in

[14] We expect positive impact of the increase in the volume of newly granted housing loans, negative impact of the increase of unemployment rate and unemployment gap and positive impact of the number of working age population on real estate prices.

the long run about 2% to 20% of the change in the volume of housing loans is transmitted into changes in real estate prices.

Chart 26 Estimated long run impact of changes in the volume of loans on real estate prices



Source: NBS.

The estimated impact of changes in the volume of newly granted loans on real estate prices is mild. The estimated decrease of the volume of newly granted housing loans in 2019 at the level of 19% is transmitted in the long run to the decrease of real estate prices at the level of 0.5% - 4.5% (Chart 26). Based on the estimated adjustment coefficients, the changes are transmitted within 5 to 9 quarters.

8. Impact of BBMs during times of increased stress

The goal of macroprudential policy is to limit the cumulation of systemic risks in the financial system. In case the cumulation of such risks is successfully curbed during "good" times, losses during "bad" times, when cumulated systemic risks materialize, will be lowered as well. This secures that during times of increased tensions the financing of the real economy by banks will not be constrained because of the lack of capital caused by excessive losses from systemic risks.

The efficiency of macroprudential policies, including BBMs, should thus be measured during times of increased stress. The efficiency of BBMs during adverse development is described in Jurča et al. (2020). Different measures impact the cumulation of systemic risks caused by the excessive loan growth and the consequent impact on banks via different channels. While DSTI limits affect the probability of default, LTV limits affect more loss given default. DTI limits impact mainly the volume of newly granted loans. The analysis confirmed also that the timely implementation of BBMs is an efficient tool for increasing the resilience of the banking sector. Last but not least, the most efficient way of curbing the cumulation of systemic risks is the combined implementation of different measures, as they are complementary to each other.

The COVID-19 pandemic is the first negative shock since BBMs have been implemented impacting the real economy and indebted population. To mitigate the impact of the virus, the government implemented several measures during 2020. For households, one of the key measures was the possible loan payment deferral for 6 to 9 months. Due to this measure, there was basically no default of retail loans in 2020. However, the analysis of households asking for this deferral can help to identify households impacted by the pandemic the most and to assess BBMs.

The characteristics of households asking for deferral until August 2020 were studied in Cupák et al. (2020)[15]. Empirical analysis confirmed that higher pre-crisis DSTI increased the probability of a household asking for deferral. The survey confirmed the pandemic negatively affected the income of most of the indebted households. A higher decrease of income increases the probability of a household asking for deferral. However, higher pre-crisis DSTI means that even a smaller decrease of income could result in a situation where a given household was not able to repay its loans.

Loan repayment deferral was analysed using individual retail loans also in (NBS, 2020). While the database of individual retail loans covers the whole portfolio of retail loans and not only part of the portfolio like the above survey data, it does not include actual changes in income or economic status of borrowers. This analysis confirms that higher risk parameters, such as higher LTV (above 80%), but mainly higher DTI (7) or DSTI (60%), are related to higher probability of asking for loan payment deferral. High DSTI and high DTI are however interconnected, while it is more the higher DSTI forcing borrowers to ask for the deferral. Borrowers with high DTI and low DSTI have a much lower share of deferral than borrowers with both high DTI and DSTI.

New retail loan defaults remained low due to deferrals. Therefore, it is not possible to assess the impact of LTV limits in the form of lower loss given default. On the other hand, deferrals justify the DSTI limit, as it curbs the share of borrowers with high instalments relative to their monthly income. It was this high DSTI causing financial problems of indebted households and forcing them to ask for deferral.

Conclusions

The National Bank of Slovakia has been actively implementing and tightening borrower-based measures since 2014. Measures cover (i) loan-to-value limits (LTV), (ii) debt service-to-income limits (DSTI) as well as (iii) debt-to-income limits (DTI). The paper provides a complex analysis of the impact of these measures on borrowers, volume of loans and partially on real estate prices.

Results are to a large extent in line with expectations and the intention of limits in case of the affected type of borrowers. DSTI limits affected mainly borrowers with at most secondary education and lower income. DTI limits affected mainly borrowers asking for a larger volume of loans and having higher education. After the implementation of the limit, the share of such borrowers within possible exceptions even increased, confirming banks granting high DTI loans mainly to this type of borrowers. LTV limits affected mainly younger borrowers aged up to 35. With gradual tightening, loans within exceptions were granted to borrowers with higher income and education. Looking at the supply side, the most binding limit in terms of the theoretical maximum value of loans was the DSTI limit, followed by LTV and DTI limits.

The impact of respective measures on the volume of newly granted loans was affected by the possible front-loading, gradual tightening of limits as well as legislative changes (mainly in 2016 related to the early loan repayment). The highest estimated impact is in 2019, when the volume of newly granted retail loans was lower by 17%. This impact, due to the still relatively high annual growth rate of the volume of loans, is relatively mild. These estimations are, on the other hand, probably affected also by the reaction of the supply and the risk management of the banks to the imposed limits. An interesting result is the higher impact of limits on housing loans in case of borrowers asking only for a housing loan compared to borrowers asking for both

[15] The analysis was conducted on a sample of indebted households selected for a survey described in Cesnak et al. (2020).

housing and consumer loans. Borrowers asking for both types of loan probably lowered the volume of consumer loans in reaction to the imposed limits.

We also estimate some impact of BBMs on the residential real estate market. Property prices are less attainable with decreasing LTV levels mainly for households without enough capital of their own. We also assume a possible decrease of real estate prices due to a decrease of the volume of newly granted housing loans. The decrease of the volume of loans in 2019 by 19% could lower real estate prices by 0.5% – 4.5%, within approximately two years. This is a relatively mild impact due to the strong real estate prices growth.

Imposed BBMs aim to curb the cumulation of systemic risks related to the excessive retail loan growth during good times. Consequently, the impact of crisis times on banks will be lower due to lower credit risk costs. Imposed limits decrease risks stemming from retail loans. LTV limits lower mainly loss given default and DSTI limits lower mainly the probability of default. DTI limits affect mainly the volume of loans.

The current pandemic is the first period of a possible materialisation of cumulated systemic risks. While LTV limits can't be assessed due to the low level of retail loan defaults because of the loan payment deferral, the pandemic justifies the imposed DSTI limits. Borrowers affected the most by the crisis were those with high pre-crisis DSTI. These borrowers asked for loan payment deferral to a larger extent than other types of borrowers.

Overall, we conclude that while the unintended consequences of BBMs are very low due to a mild impact on the volume of loans as well as on real estate prices, the current pandemic justifies the implementation of the measures.

Literature

Ahuja, A. and Nabar, M. (2011). Safeguarding Banks and Containing Property Booms: Cross-Country Evidence on Macroprudential Policies and Lessons from Hong Kong SAR. *IMF Working Paper, WP/11/284*.

Anenberg, E., Hizmo, A., Kung, E. and Molloy, R. (2019). Measuring mortgage credit availability: A frontier estimation approach. *Journal of Applied Econometrics, 34*(6), pp. 865-882.

Belotti, F., Daidone, S., Ilardi, G. and Atella, V. (2013). Stochastic Frontier Analysis using Stat. *The Stata Journal, 13*(4).

Cassidy, M. and Hallissey, N. (2016). The Introduction of Macroprudential Measures for the Irish Mortgage Market. *The Economic and Social Review, 47*(2), pp. 271-297.

Cesnak, M., Cupák, A., Jurašeková Kucserová, J., Jurča, P., Klacso, J., Košútová, A., Moravčík, A. and Šuster, M. (2020). Vplyv koronakrízy na finančnú situáciu a očakávania zadlžených domácností. *NBS Occasional paper, 3/2020*.

Cesnak, M. and Klacso, J. (2021). Assessing real estate prices in Slovakia - a structural approach. *NBS Working paper, 3/2021*.

Cupák, A., Klacso, J. and Šuster, M. (2020). Surveying the Impact of the Covid-19 Recession on the Financial Situation of Indebted Households. *NBS Working paper, 6/2020*.

Gross, M. and Población, J. (2017). Assessing the Efficacy of Borrower-Based Macroprudential Policy Using an Integrated Micro-Macro Model for European Households. *Economic Modelling, 61*, pp. 510-528.

Harrison, O., Jurča, P., Rychtárik, Š. and Yackovlev, I. (2018). Credit Growth and Macroprudential Policies in the Slovak Republic. *V: IMF Country Report, 18*(242). Slovak Republic.

Chawla, N. V., Bowyer, K. W., Hall, L. O. and Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research, 16*, pp. 321-357.

Igan, D. and Kang, H. (2011). Do Loan-to-Value and Debt-to-Income Limits Work? Evidence from Korea. *IMF Working Paper, WP/11/297*.

Jurča, P., Klacso, J., Tereanu, E., Forletta, M. and Gross, M. (2020). The Efectiveness of Borrower-Based Macroprudential Measures: A Quantitative Analysis for Slovakia. *IMF Working Paper, WP/20/134*.

Kelly, R. and Mazza, E. (2019). *Measuring Mortgage Availability & Take-Up: An Application to Macro-Prudential Policy.* Central Bank of Ireland.

Kelly, R., McCann, F. and O'Toole, C. (2015). Credit conditions, macroprudential policy and house prices. *Research Technical Paper, 6/RT/15*.

Kuttner, K. and Shim, I. (2012). Taming the Real Estate Beast: The Effects of Monetary and Macroprudential Policies on Housing Prices and Credit. *RBA Annual Conference, in: Alexandra Heath a Frank Packer a Callan Windsor, Property Markets and Financial Stability, Reserve Bank of Australia.*

National Bank of Slovakia. (2014). Financial Stability Report. *November 2014*.

National Bank of Slovakia. (2017). Financial Stability Report. *November 2017*.

National Bank of Slovakia. (2019). Financial Stability Report. *November 2019*.

National Bank of Slovakia. (2020). Financial Stability Report. *November 2020*.

Richter, B., Schularick, M. and Shim, I. (2018). The Costs of Macroprudential Policy. *NBER Working paper 24989*.

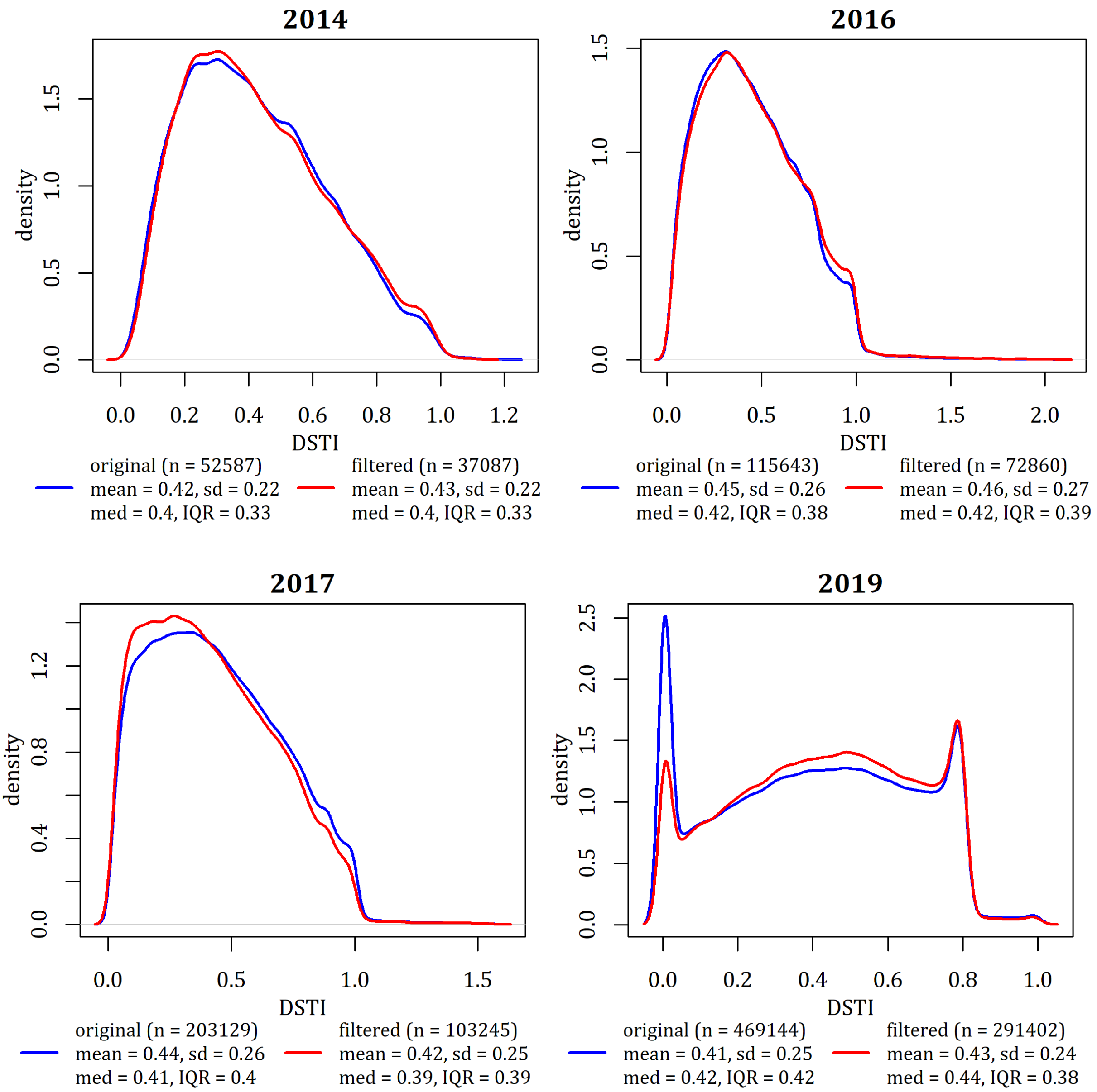
Vandenbussche, J., Vogel, U. and Detragiache, E. (2015). Macroprudential Policies and Housing Prices: A New Database and Empirical Evidence for Central, Eastern, and Southeastern Europe. *Journal of Money, Credit and Banking, 47*(1), pp. 343-377.

Appendix 1 Variables used in empirical analysis

Variable	Definition
DSTI	DSTI at the date of the last loan origination in a given year.
DTI	DTI at the date of the last loan origination in a given year.
LTV	LTV at the date of loan origination.
Education	Highest education among all borrowers at the time of the last loan origination in a given year: PE – at most primary SE – at most secondary TE – tertiary
Age	Average age of all co-debtors at the time of the last loan origination in a given year.
Income_source	Main source of income of the co-debtor with the highest income at the time of the last loan origination in a given year: SE – self-employed EM – employed SOC – pensioner, parental leave, other social benefits, other income source EI&WI – economically inactive or without income
Region	Region, where the underlying collateral is located: BA, TT, TN, NR, BB, ZA, PO, KE.
Income	Sum of income of all co-debtors at the time of the last loan origination in a given year.
Instalments	Sum of instalments of all loans granted in a given year.
Debt	Sum of all loans granted in a given year.
Consumer_loans	Number of consumer loans granted in a given year.
Housing_loans	Number of housing loans granted in a given year.
Borrowers	Average number of co-debtors of all loans granted in a given year weighted by the amount of loan (for DTI analysis) or amount of instalments (for DSTI analysis).

Note: for DSTI or DTI analysis loans are connected based on the same main debtor. For LTV analysis all loans are analysed separately.

Appendix 2 Newly granted loans – distribution based on DSTI



Note: original data = raw data with outliers cleared and missing values, filtered data = data filtered from original data, used in regressions and decision trees. Distributions were smoothed using the Kernel method, bandwidth parameter chosen based on the Silverman rule for each selection.

Appendix 3 Logit regressions - DSTI

2016	$Y = \begin{cases} 0; DSTI \leq 0.8 \\ 1; DSTI > 0.8 \end{cases}$			$Y = \begin{cases} 0; DSTI \in \langle 0.6, 0.8 \rangle \\ 1; DSTI > 0.8 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	20.799***	12.397***	-5.094***	17.173***	9.282***	1.018***
	(0.33)	(0.255)	(0.133)	(0.402)	(0.301)	(0.192)
Reference category: SE						
Education = PE	0.282***	0.176**	0.859***	0.171*	0.155*	0.348***
	(0.072)	(0.062)	(0.059)	(0.08)	(0.078)	(0.076)
Education = TE	-0.114**	-0.1*	-0.862***	-0.019	-0.014	-0.266***
	(0.043)	(0.039)	(0.036)	(0.045)	(0.044)	(0.042)
Age	0.003*	0.012***	-0.011***	0.001	0.006***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Reference category: EM						
Income_source = SE	0.567***	0.534***	0.513***	0.446***	0.403***	0.411***
	(0.059)	(0.053)	(0.048)	(0.064)	(0.061)	(0.058)
Income_source = SOC	0.105*	0.054	1.064***	-0.029	0.006	0.356***
	(0.051)	(0.046)	(0.041)	(0.056)	(0.055)	(0.052)
Income_source = EI&WI	1.976	0.879	0.102	0.953	-0.598	-1.059
	(1.993)	(1.207)	(1.1)	(1.608)	(1.194)	(1.15)
Income (log10)	-15.921***	-9.009***		-11.384***	-5.263***	
	(0.179)	(0.117)		(0.244)	(0.142)	
Instalments (log10)	8.512***		2.213***	5.264***		-0.492***
	(0.117)		(0.054)	(0.157)		(0.079)
Debt (log10)	-0.065	2.089***	-0.346***	-0.18**	0.796***	-0.15**
	(0.052)	(0.042)	(0.034)	(0.062)	(0.056)	(0.055)
Consumer_loans	0.01	0.015	-0.046	0.082	0.056	0.004
	(0.042)	(0.038)	(0.035)	(0.046)	(0.043)	(0.04)
Housing_loans	-0.045	-0.216***	-0.02	0.108	-0.259***	-0.174***
	(0.053)	(0.046)	(0.041)	(0.058)	(0.054)	(0.052)
Borrowers	1.636***	1.292***	-0.197***	1.592***	1.056***	0.346***
	(0.042)	(0.036)	(0.029)	(0.048)	(0.042)	(0.035)
Pseudo R^2	0.37	0.2	0.07	0.13	0.08	0.02
Number of observations	72,860	72,860	72,860	21,003	21,003	21,003

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

2017	$Y = \begin{cases} 0; DSTI \leq 0.8 \\ 1; DSTI > 0.8 \end{cases}$			$Y = \begin{cases} 0; DSTI \in \langle 0.6, 0.8 \rangle \\ 1; DSTI > 0.8 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	23.397***	13.263***	-5.811***	18.073***	10.593***	1.927***
	(0.323)	(0.243)	(0.121)	(0.366)	(0.282)	(0.176)
Reference category: SE						
Education = PE	0.21**	0.159*	0.755***	0.153*	0.11	0.26***
	(0.072)	(0.062)	(0.059)	(0.078)	(0.076)	(0.074)
Education = TE	0.009	-0.033	-0.833***	0.096*	0.055	-0.236***
	(0.039)	(0.035)	(0.033)	(0.041)	(0.04)	(0.037)
Age	0	0.007***	-0.013***	-0.001	0.003*	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Reference category: EM						
Income_source = SE	0.573***	0.517***	0.615***	0.464***	0.45***	0.543***
	(0.055)	(0.048)	(0.043)	(0.057)	(0.055)	(0.051)
Income_source = SOC	0.116*	0.002	1.178***	-0.016	-0.044	0.421***
	(0.049)	(0.044)	(0.039)	(0.053)	(0.052)	(0.049)
Income_source = EI&WI	-3.985	-7.729	-6.499	-	-	-
	(74.726)	(77.012)	(47.92)	-	-	-
Income (log10)	-18.03***	-9.259***		-11.643***	-5.223***	
	(0.184)	(0.109)		(0.227)	(0.127)	
Instalments (log10)	9.814***		2.362***	5.375***		-0.495***
	(0.12)		(0.05)	(0.147)		(0.068)
Debt (log10)	-0.015	2.093***	-0.264***	-0.22***	0.512***	-0.337***
	(0.046)	(0.036)	(0.029)	(0.05)	(0.047)	(0.044)
Consumer_loans	-0.052	-0.022	-0.061*	0.018	0.02	-0.018
	(0.033)	(0.029)	(0.027)	(0.034)	(0.032)	(0.03)
Housing_loans	0.315***	0.143***	0.199***	0.361***	0.057	0.067
	(0.04)	(0.034)	(0.031)	(0.042)	(0.04)	(0.038)
Borrowers	1.663***	1.186***	-0.367***	1.37***	0.862***	0.182***
	(0.042)	(0.035)	(0.029)	(0.045)	(0.04)	(0.035)
Pseudo R^2	0.4	0.21	0.08	0.13	0.08	0.02
Number of observations	103,218	103,218	103,218	26,095	26,095	26,095

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

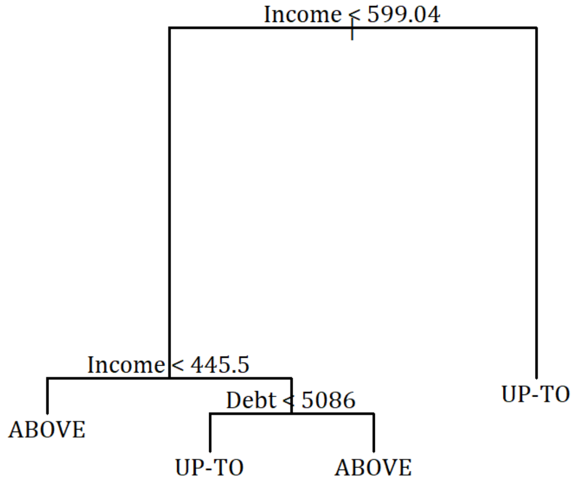
2019	$Y = \begin{cases} 0; DSTI \leq 0.6 \\ 1; DSTI > 0.6 \end{cases}$			$Y = \begin{cases} 0; DSTI \in \langle 0.4, 0.6 \rangle \\ 1; DSTI > 0.6 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	11.068***	6.121***	-4.856***	8.574***	6.26***	-1.163***
	(0.09)	(0.078)	(0.039)	(0.099)	(0.091)	(0.046)
Reference category: SE						
Education = PE	0.163***	0.203***	0.399***	0.056	0.118***	0.237***
	(0.028)	(0.026)	(0.024)	(0.032)	(0.032)	(0.03)
Education = TE	-0.056***	-0.092***	-0.625***	-0.048***	-0.056***	-0.37***
	(0.013)	(0.012)	(0.011)	(0.014)	(0.013)	(0.013)
Age	0.004***	0.011***	0.00	0.002**	0.005***	0.00
	(0.00)	(0.00)	(0.00)	(0.001)	(0.001)	(0.00)
Reference category: EM						
Income_source = SE	0.377***	0.297***	-0.147***	0.356***	0.31***	0.17***
	(0.023)	(0.022)	(0.02)	(0.025)	(0.025)	(0.024)
Income_source = SOC	-0.112***	-0.19***	0.641***	-0.247***	-0.229***	0.318***
	(0.019)	(0.018)	(0.017)	(0.021)	(0.021)	(0.02)
Income_source = EI&WI	-3.718***	-3.498***	-2.347***	0.602**	0.742***	0.51*
	(0.137)	(0.136)	(0.135)	(0.208)	(0.208)	(0.202)
Income (log10)	-8.371***	-5.137***		-4.994***	-3.47***	
	(0.044)	(0.033)		(0.046)	(0.037)	
Instalments (log10)	4.576***		1.183***	2.028***		0.245***
	(0.031)		(0.02)	(0.031)		(0.023)
Debt (log10)	0.145***	1.684***	0.339***	0.101***	0.77***	0.171***
	(0.013)	(0.01)	(0.012)	(0.015)	(0.011)	(0.014)
Consumer_loans	0.002	0.029***	0.006	0.01	0.026**	0.014
	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)	(0.009)
Housing_loans	-0.006	-0.466***	-0.387***	-0.301***	-0.511***	-0.547***
	(0.014)	(0.014)	(0.013)	(0.015)	(0.015)	(0.015)
Borrowers	0.904***	0.695***	-0.1***	0.709***	0.578***	0.054***
	(0.015)	(0.014)	(0.013)	(0.016)	(0.015)	(0.014)
Pseudo R^2	0.22	0.15	0.07	0.08	0.06	0.02
Number of observations	291,368	291,368	291,368	162,236	162,236	162,236

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

Appendix 4 Decision trees - DSTI

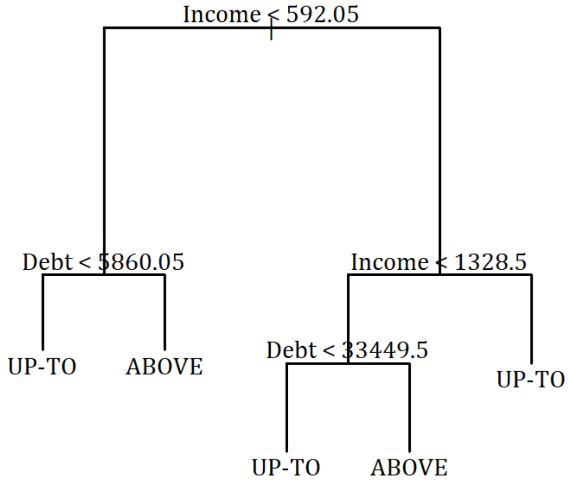
Oversampling using minority sample replication method[1]

2014 –DSTI limit = 80%



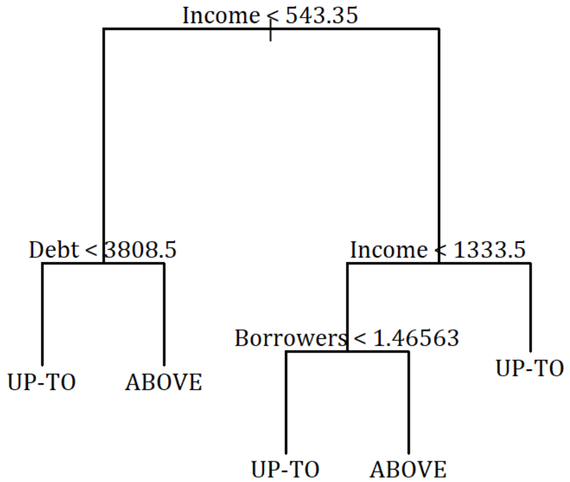
Distribution: UP-TO : ABOVE = 34605 : 2476
Missclassification error rate = 19.29 %
Balanced missclassification error rate = 24.89 %

2015 –DSTI limit = 80%



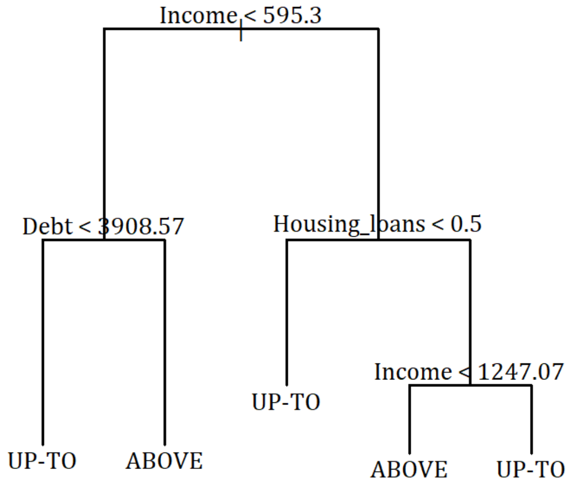
Distribution: UP-TO : ABOVE = 42893 : 6096
Missclassification error rate = 37.4 %
Balanced missclassification error rate = 30.48 %

2016 –DSTI limit = 80%



Distribution: UP-TO : ABOVE = 64741 : 8119
Missclassification error rate = 30.53 %
Balanced missclassification error rate = 29.57 %

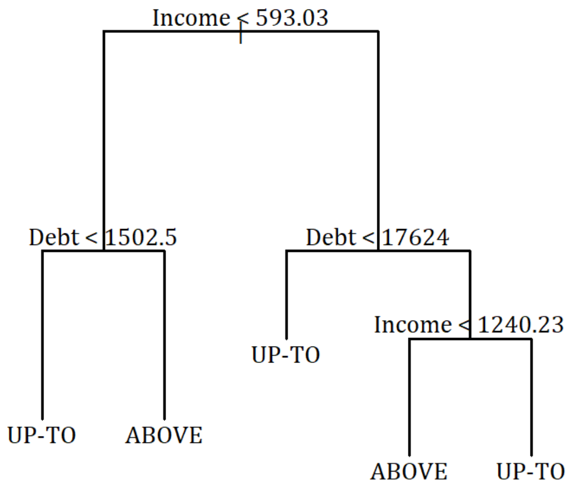
2017 –DSTI limit = 80%



Distribution: UP-TO : ABOVE = 94129 : 9089
Missclassification error rate = 26.72 %
Balanced missclassification error rate = 25.83 %

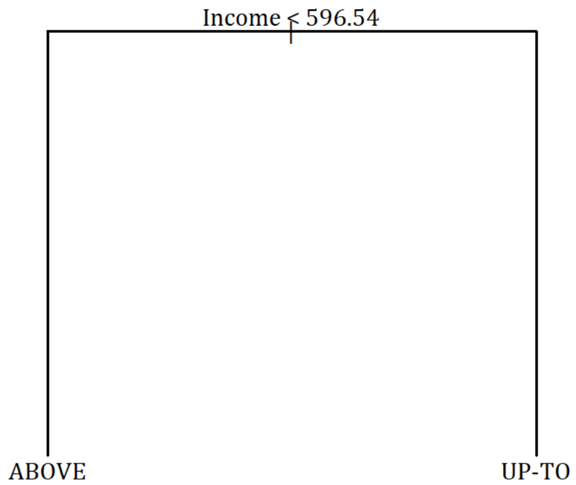
[1] Due to the problem of unbalanced dataset with respect to the explanatory variables, models were trained on datasets modified using the minority sample replication method. Misclassification error rates were evaluated using original unbalanced datasets. The number of replications as well as the number of end nodes were selected in order to optimize models' error rate indicators (misclassification error rate and balanced misclassification error rate).

2018 – DSTI limit = 80%



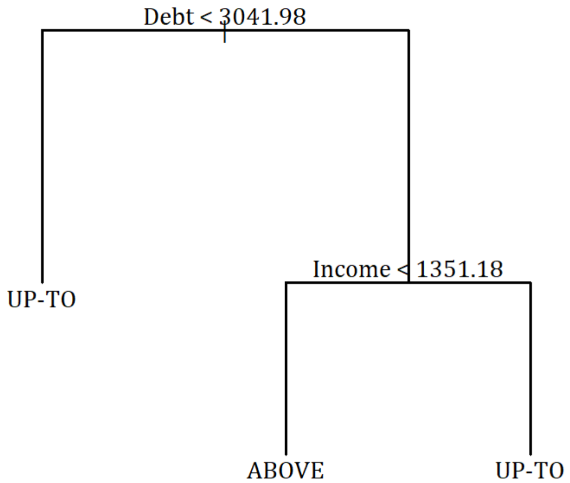
Distribution: UP-TO : ABOVE = 225133 : 17380
Missclassification error rate = 35.51 %
Balanced missclassification error rate = 32.57 %

2019 – DSTI limit = 80%



Distribution: UP-TO : ABOVE = 287674 : 3694
Missclassification error rate = 19.33 %
Balanced missclassification error rate = 34.35 %

2019 – DSTI limit = 60%

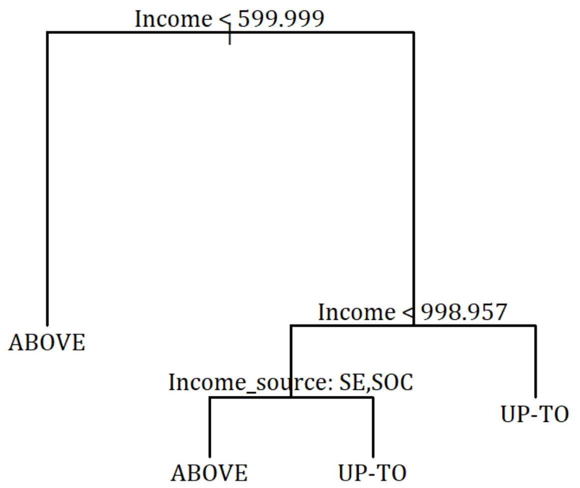


Distribution: UP-TO : ABOVE = 208858 : 82510
Missclassification error rate = 38.58 %
Balanced missclassification error rate = 34.99 %

Note: Housing_loans < 1 means, that borrower doesn't have a housing loan.

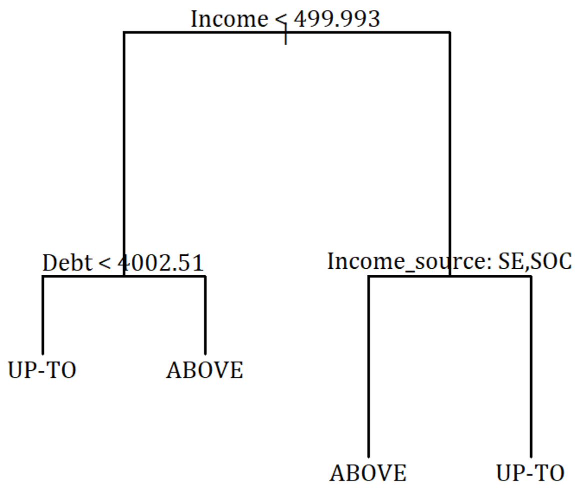
Oversampling and undersampling using SMOTE method [2]

2014 – DSTI limit = 80%



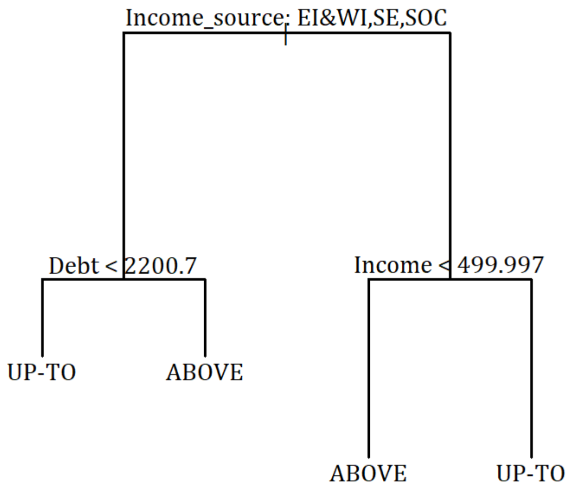
Distribution: UP-TO : ABOVE = 34605 : 2476
Missclassification error rate = 26.84 %
Balanced missclassification error rate = 26.29 %

2015 – DSTI limit = 80%



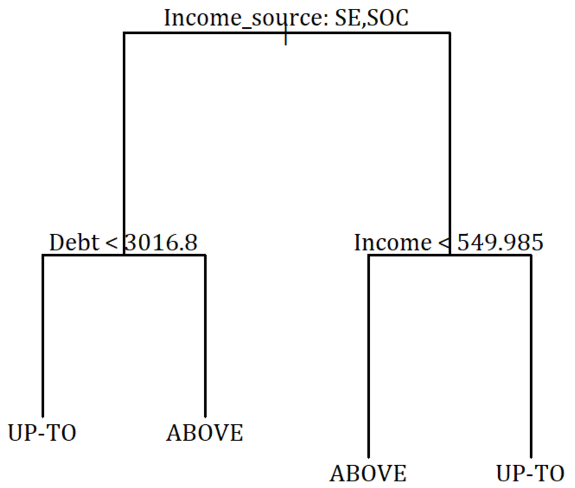
Distribution: UP-TO : ABOVE = 42893 : 6096
Missclassification error rate = 23.04 %
Balanced missclassification error rate = 37.03 %

2016 – DSTI limit = 80%



Distribution: UP-TO : ABOVE = 64741 : 8119
Missclassification error rate = 23.72 %
Balanced missclassification error rate = 35.61 %

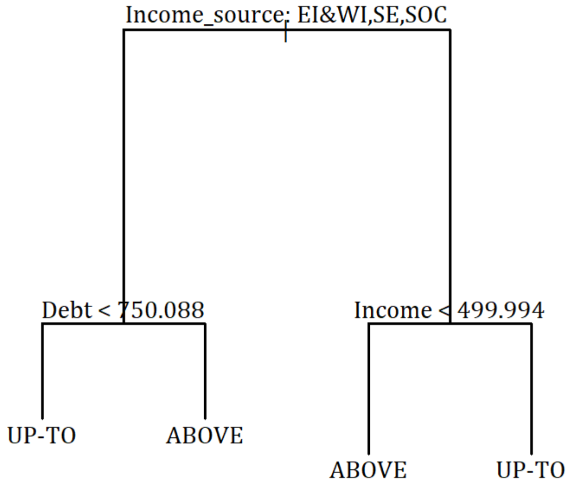
2017 – DSTI limit = 80%



Distribution: UP-TO : ABOVE = 94129 : 9089
Missclassification error rate = 25.36 %
Balanced missclassification error rate = 34.48 %

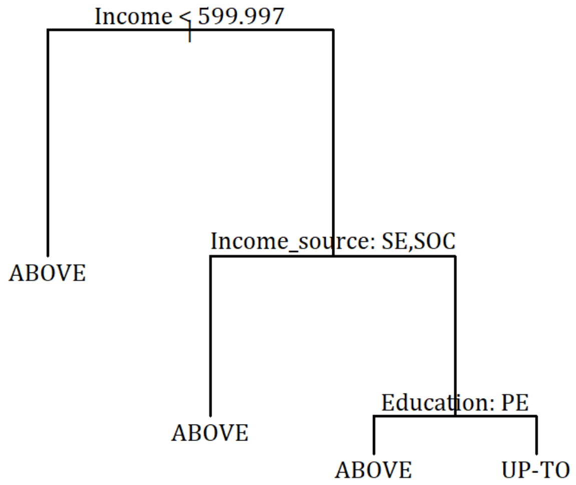
[2] Due to the problem of unbalanced dataset with respect to the explanatory variable, models were trained on datasets modified using the SMOTE method. Misclassification error rates were evaluated using original unbalanced datasets. The number of replications as well as the number of end nodes were selected in order to optimize models' error rate indicators (misclassification error rate and balanced misclassification error rate). A detailed description and use of the SMOTE method is provided in Chawla et al. (2002).

2018 – DSTI limit = 80%



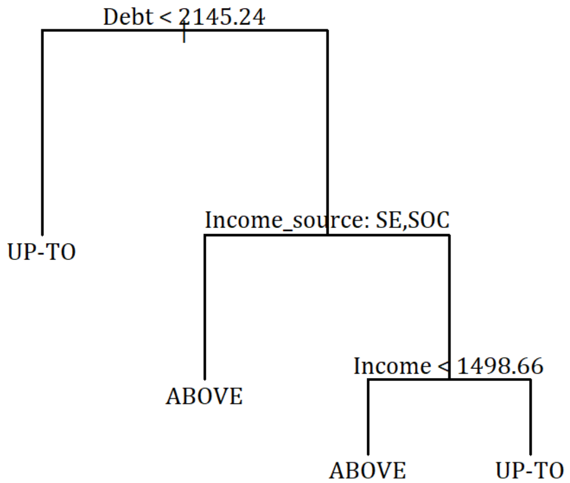
Distribution: UP-TO : ABOVE = 225133 : 17380
Missclassification error rate = 22.01 %
Balanced missclassification error rate = 39.52 %

2019 – DSTI limit = 80%



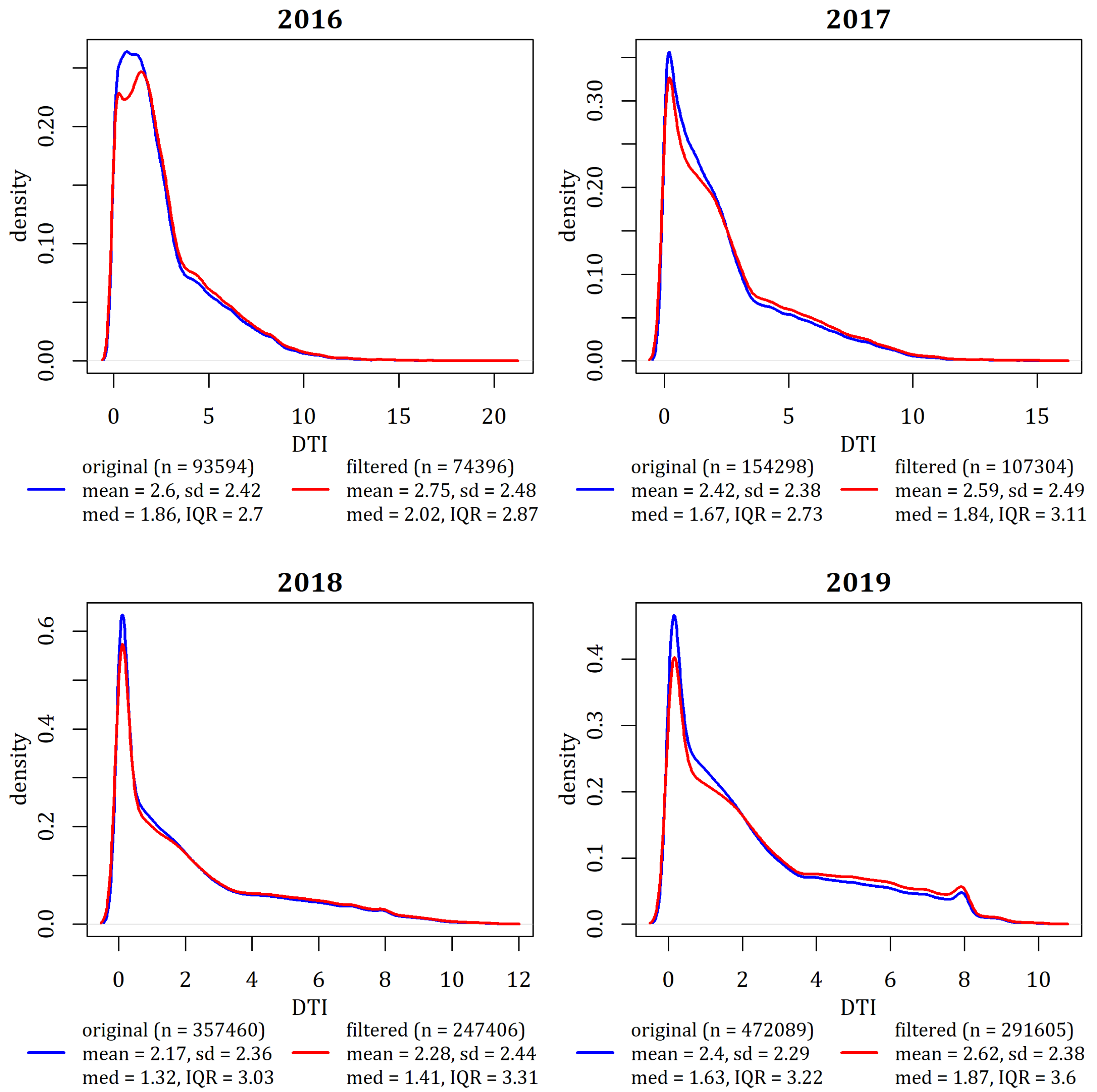
Distribution: UP-TO : ABOVE = 287674 : 3694
Missclassification error rate = 28.37 %
Balanced missclassification error rate = 35.96 %

2019 – DSTI limit = 60%



Distribution: UP-TO : ABOVE = 208858 : 82510
Missclassification error rate = 44 %
Balanced missclassification error rate = 36.42 %

Appendix 5 Newly granted loans – distribution based on DTI



Note: original data = raw data with outliers cleared and missing values, filtered data = data filtered from original data, used in regressions and decision trees. Distributions were smoothed using the Kernel method, bandwidth parameter chosen based on the Silverman rule for each selection.

Appendix 6 Logit regressions – DTI, borrowers with at least one housing loan

2016	$Y = \begin{cases} 0; DTI \leq 8 \\ 1; DTI > 8 \end{cases}$			$Y = \begin{cases} 0; DSTI \in \langle 7, 8 \rangle \\ 1; DSTI > 8 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-108.475***	7.982***	-46.374***	-232.403***	4.975***	-27.414***
	(2.977)	(0.434)	(0.901)	(8.78)	(0.63)	(1.322)
Reference category: SE						
Education = PE	1.456	0.549	0.707	2.177	2.916*	1.462
	(1.028)	(0.435)	(0.546)	(2.074)	(1.371)	(1.095)
Education = TE	0.086	0.44***	-0.532***	-0.008	0.282***	-0.109
	(0.096)	(0.05)	(0.054)	(0.148)	(0.069)	(0.07)
Age	-0.014	-0.107***	-0.067***	-0.007	-0.033***	-0.016**
	(0.007)	(0.003)	(0.004)	(0.011)	(0.005)	(0.005)
Reference category: EM						
Income_source = SE	-0.162	0.071	0.085	0.087	-0.044	0.101
	(0.152)	(0.08)	(0.086)	(0.237)	(0.106)	(0.11)
Income_source = SOC	-0.937*	-0.602**	0.082	-0.545	-0.307	0.08
	(0.403)	(0.201)	(0.215)	(0.632)	(0.276)	(0.287)
Income_source = EI&WI	-12.093	-8.052	-10.621	-	-	-
	(183529.235)	(103.143)	(111.845)	-	-	-
Income (log10)	-48.177***	-10.226***		-116.089***	-5.595***	
	(1.268)	(0.237)		(4.314)	(0.374)	
Instalments (log10)	-2.356***	9.701***	-5.045***	-0.273	5.126***	-3.763***
	(0.384)	(0.196)	(0.188)	(0.588)	(0.305)	(0.327)
Debt (log10)	52.257***		12.715***	116.806***		7.902***
	(1.352)		(0.254)	(4.337)		(0.393)
Consumer_loans	-0.134	-0.031	-0.12	-0.06	-0.048	-0.099
	(0.173)	(0.088)	(0.092)	(0.281)	(0.113)	(0.116)
Housing_loans	0.062	-0.462**	-0.43**	-0.132	-0.269	-0.252
	(0.254)	(0.147)	(0.158)	(0.407)	(0.189)	(0.196)
Borrowers	-0.652***	-0.386***	-0.98***	-0.205	-0.096	-0.352***
	(0.099)	(0.051)	(0.053)	(0.149)	(0.069)	(0.071)
Pseudo R^2	0.82	0.32	0.42	0.78	0.06	0.1
Number of observations	24,489	24,489	24,489	4,714	4,714	4,714

Note: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors in parenthesis.

2017	$Y = \begin{cases} 0; DTI \leq 8 \\ 1; DTI > 8 \end{cases}$			$Y = \begin{cases} 0; DSTI \in \langle 7, 8 \rangle \\ 1; DSTI > 8 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-106.232***	7.002***	-40.992***	-249.483***	3.938***	-25.216***
	(2.539)	(0.372)	(0.736)	(8.527)	(0.549)	(1.14)
Reference category: SE						
Education = PE	0.152	-1.152*	-0.259	0.65	-1.017	-0.603
	(0.947)	(0.496)	(0.549)	(1.342)	(0.599)	(0.629)
Education = TE	-0.05	0.367***	-0.573***	-0.1	0.184**	-0.23***
	(0.084)	(0.044)	(0.048)	(0.13)	(0.061)	(0.063)
Age	-0.013*	-0.088***	-0.065***	0	-0.021***	-0.02***
	(0.006)	(0.003)	(0.003)	(0.009)	(0.004)	(0.004)
Reference category: EM						
Income_source = SE	-0.144	0.036	0.084	-0.336	-0.028	0.176
	(0.131)	(0.069)	(0.077)	(0.202)	(0.095)	(0.099)
Income_source = SOC	-0.925*	-0.52**	-0.04	-0.571	-0.573*	-0.529*
	(0.387)	(0.186)	(0.213)	(0.74)	(0.237)	(0.251)
Income_source = EI&WI	16.271	-7.681	-4.798	-	-	-
	(1455.398)	(119.468)	(119.468)	-	-	-
Income (log10)	-47.847***	-8.741***		-125.085***	-3.519***	
	(1.102)	(0.204)		(4.265)	(0.292)	
Instalments (log10)	-1.869***	8.214***	-3.504***	-0.158	3.08***	-3.059***
	(0.285)	(0.161)	(0.14)	(0.446)	(0.218)	(0.258)
Debt (log10)	51.384***		10.796***	125.587***		7.136***
	(1.16)		(0.199)	(4.251)		(0.327)
Consumer_loans	0.039	-0.016	-0.063	0.046	0.006	0.005
	(0.109)	(0.056)	(0.062)	(0.18)	(0.079)	(0.082)
Housing_loans	-0.075	0.011	0.013	-0.196	0.022	0.06
	(0.197)	(0.107)	(0.113)	(0.296)	(0.149)	(0.155)
Borrowers	-0.738***	-0.644***	-1.495***	-0.296*	-0.265***	-0.761***
	(0.09)	(0.046)	(0.049)	(0.139)	(0.064)	(0.068)
Pseudo R^2	0.8	0.27	0.39	0.78	0.04	0.09
Number of observations	27,449	27,449	27,449	5,962	5,962	5,962

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

2018	$Y = \begin{cases} 0; DTI \leq 8 \\ 1; DTI > 8 \end{cases}$			$Y = \begin{cases} 0; DSTI \in (7,8\rangle \\ 1; DSTI > 8 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-40.434***	7.719***	-28.11***	-34.913***	5.656***	-9.939***
	(0.777)	(0.286)	(0.474)	(1.101)	(0.379)	(0.633)
Reference category: SE						
Education = PE	-0.271	-0.983*	-0.073	-0.394	-0.792	-0.414
	(0.443)	(0.4)	(0.397)	(0.481)	(0.473)	(0.456)
Education = TE	0.216***	0.517***	-0.293***	0.201***	0.282***	0.004
	(0.041)	(0.034)	(0.033)	(0.046)	(0.041)	(0.04)
Age	-0.042***	-0.089***	-0.074***	-0.021***	-0.036***	-0.034***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Reference category: EM						
Income_source = SE	0.066	0.092	-0.365***	0.007	0.024	-0.009
	(0.066)	(0.054)	(0.054)	(0.073)	(0.065)	(0.064)
Income_source = SOC	-0.34*	-0.284*	-0.666***	-0.485**	-0.491***	-0.538***
	(0.141)	(0.117)	(0.119)	(0.147)	(0.133)	(0.133)
Income_source = EI&WI	-0.099	-0.838	-0.434	0.27	0.85	0.898
	(0.877)	(0.654)	(0.66)	(1.228)	(1.162)	(1.182)
Income (log10)	-22.017***	-11.586***		-22.53***	-7.453***	
	(0.322)	(0.189)		(0.522)	(0.295)	
Instalments (log10)	2.157***	10.955***	-2.7***	3.235***	6.758***	-0.529***
	(0.199)	(0.162)	(0.108)	(0.251)	(0.251)	(0.158)
Debt (log10)	20.439***		7.552***	18.939***		2.615***
	(0.311)		(0.136)	(0.488)		(0.187)
Consumer_loans	0.005	-0.037	-0.083**	0.013	0.023	0.042
	(0.034)	(0.028)	(0.027)	(0.038)	(0.034)	(0.034)
Housing_loans	0.119	0.069	0.103	0.043	0.039	0.084
	(0.088)	(0.072)	(0.07)	(0.098)	(0.089)	(0.087)
Borrowers	-0.495***	-0.548***	-1.08***	-0.089	-0.191***	-0.55***
	(0.044)	(0.036)	(0.034)	(0.049)	(0.044)	(0.043)
Pseudo R^2	0.53	0.3	0.24	0.21	0.07	0.04
Number of observations	50,345	50,345	50,345	11,681	11,681	11,681

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

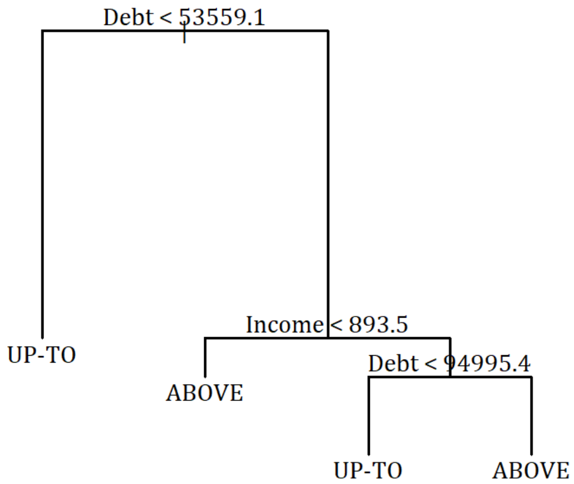
2019	$Y = \begin{cases} 0; DTI \leq 8 \\ 1; DTI > 8 \end{cases}$			$Y = \begin{cases} 0; DSTI \in (7, 8\rangle \\ 1; DSTI > 8 \end{cases}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.664***	2.372***	-2.498***	0.784	-0.695	0.536*
	(0.361)	(0.3)	(0.253)	(0.446)	(0.362)	(0.229)
Reference category: SE						
Education = PE	-2.161*	-2.191*	-2.058*	-1.831	-1.769	-1.823
	(0.999)	(0.999)	(0.999)	(1.021)	(1.02)	(1.021)
Education = TE	0.683***	0.697***	0.551***	0.541***	0.528***	0.535***
	(0.039)	(0.039)	(0.038)	(0.043)	(0.043)	(0.042)
Age	-0.08***	-0.083***	-0.088***	-0.039***	-0.037***	-0.039***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Reference category: EM						
Income_source = SE	-0.057	-0.054	-0.198**	-0.26***	-0.267***	-0.263***
	(0.067)	(0.067)	(0.067)	(0.072)	(0.071)	(0.071)
Income_source = SOC	0.023	0.026	-0.055	-0.245	-0.25	-0.248
	(0.12)	(0.12)	(0.12)	(0.128)	(0.128)	(0.128)
Income_source = EI&WI	-0.824	-0.844	-0.883	0.252	0.237	0.246
	(0.718)	(0.717)	(0.718)	(0.843)	(0.843)	(0.843)
Income (log10)	-2.163***	-2.193***		-0.098	0.221	
	(0.126)	(0.125)		(0.151)	(0.139)	
Instalments (log10)	1.55***	1.862***	0.584***	0.795***	-0.004	0.743***
	(0.12)	(0.083)	(0.1)	(0.156)	(0.06)	(0.133)
Debt (log10)	0.277***		0.399***	-0.521***		-0.498***
	(0.079)		(0.073)	(0.092)		(0.084)
Consumer_loans	-0.197***	-0.21***	-0.185***	-0.046	-0.037	-0.046
	(0.035)	(0.035)	(0.035)	(0.038)	(0.038)	(0.038)
Housing_loans	-0.149	-0.151	-0.199*	-0.097	-0.094	-0.098
	(0.096)	(0.096)	(0.095)	(0.105)	(0.105)	(0.105)
Borrowers	-0.479***	-0.488***	-0.691***	-0.126**	-0.132**	-0.137**
	(0.041)	(0.041)	(0.039)	(0.047)	(0.047)	(0.043)
Pseudo R^2	0.09	0.09	0.08	0.02	0.02	0.02
Number of observations	75,630	75,630	75,630	15,017	15,017	15,017

Note: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors in parenthesis.

Appendix 7 Decision trees – DTI

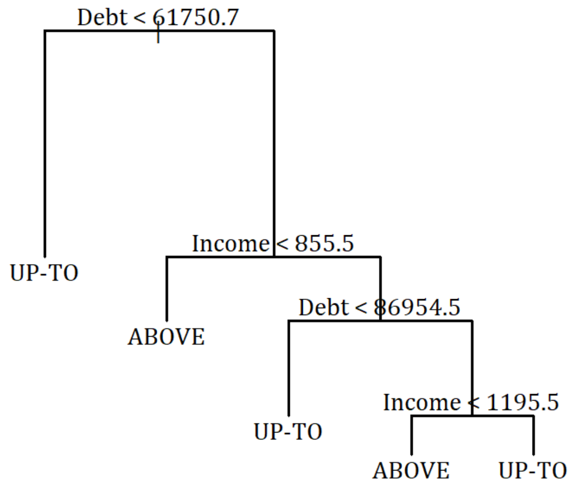
Oversampling using minority sample replication method

2016 – DTI limit = 8



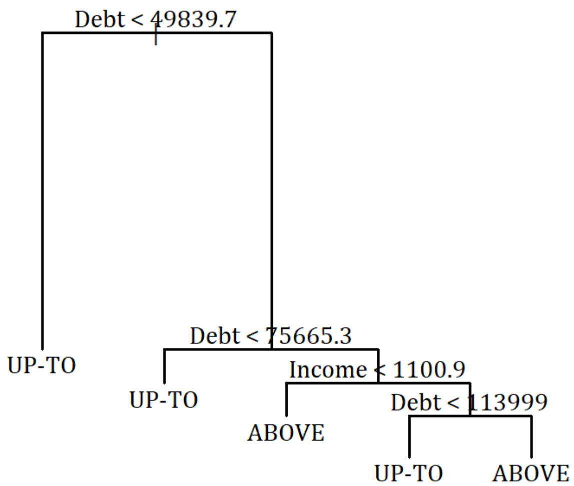
Distribution: UP-TO : ABOVE = 71135 : 3261
Missclassification error rate = 6.81 %
Balanced missclassification error rate = 6.85 %

2016 – DTI limit = 8 (Borrowers with housing loans)



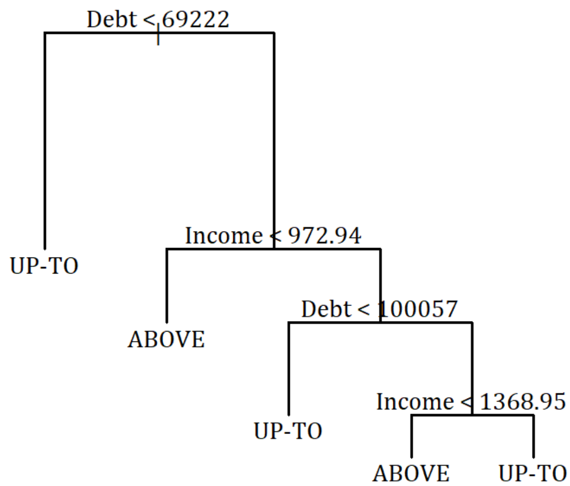
Distribution: UP-TO : ABOVE = 21488 : 3001
Missclassification error rate = 8.01 %
Balanced missclassification error rate = 17.39 %

2017– DTI limit = 8



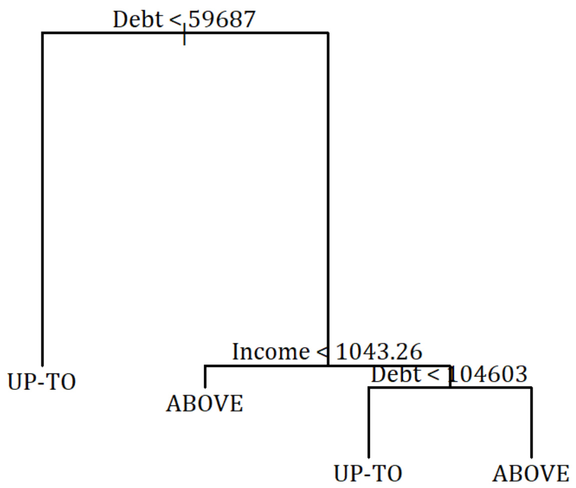
Distribution: UP-TO : ABOVE = 102605 : 4699
Missclassification error rate = 4.85 %
Balanced missclassification error rate = 13.42 %

2017 – DTI limit = 8 (Borrowers with housing loans)



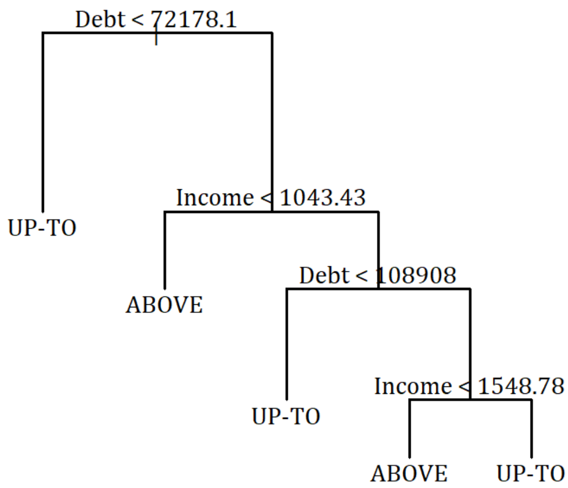
Distribution: UP-TO : ABOVE = 23628 : 3821
Missclassification error rate = 8.78 %
Balanced missclassification error rate = 17.87 %

2018 – DTI limit = 8



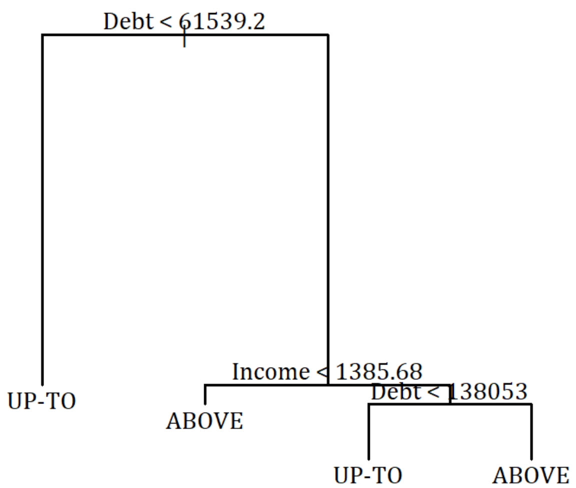
Distribution: UP-TO : ABOVE = 239735 : 7671
Missclassification error rate = 8.96 %
Balanced missclassification error rate = 8.02 %

2018 – DTI limit = 8 (Borrowers with housing loans)



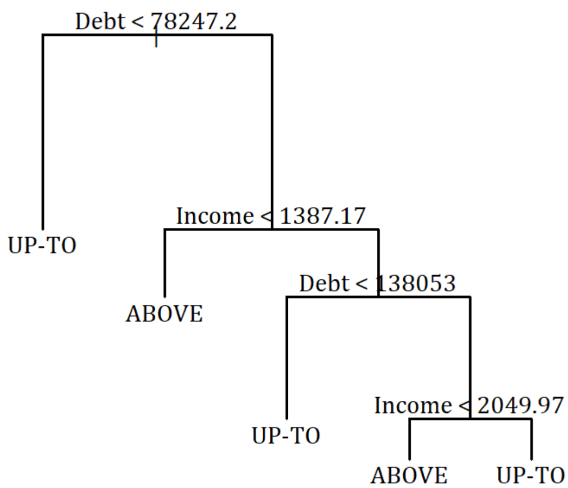
Distribution: UP-TO : ABOVE = 44420 : 5925
Missclassification error rate = 11.9 %
Balanced missclassification error rate = 21.67 %

2019 – DTI limit = 8



Distribution: UP-TO : ABOVE = 286948 : 4657
Missclassification error rate = 12.07 %
Balanced missclassification error rate = 15.08 %

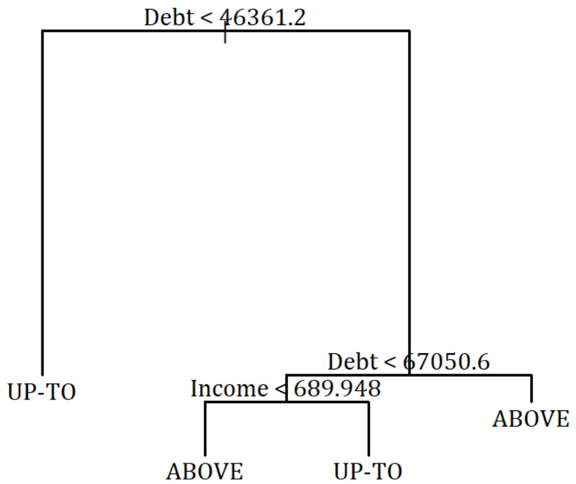
2019 – DTI limit = 8 (Borrowers with housing loans)



Distribution: UP-TO : ABOVE = 72392 : 3238
Missclassification error rate = 15.5 %
Balanced missclassification error rate = 27.98 %

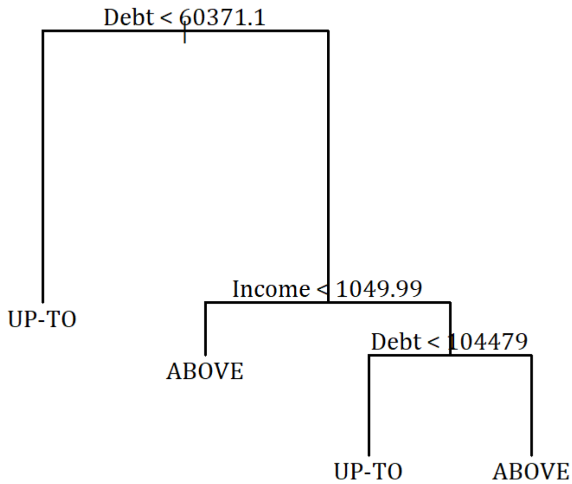
Oversampling and undersampling using SMOTE method

2016 – DTI limit = 8



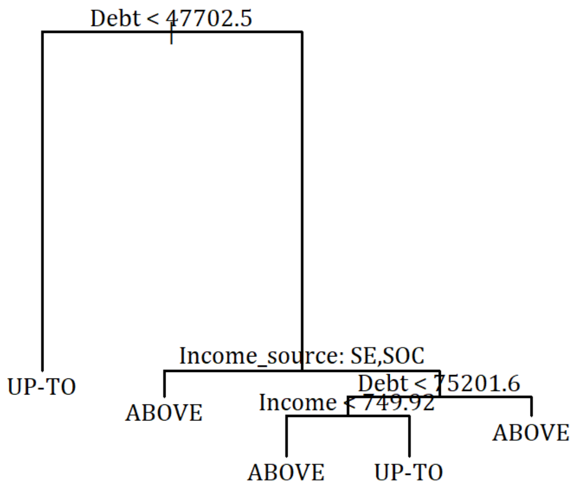
Distribution: UP-TO : ABOVE = 71135 : 3261
Missclassification error rate = 11.18 %
Balanced missclassification error rate = 6.73 %

2016 – DTI limit = 8 (Borrowers with housing loan)



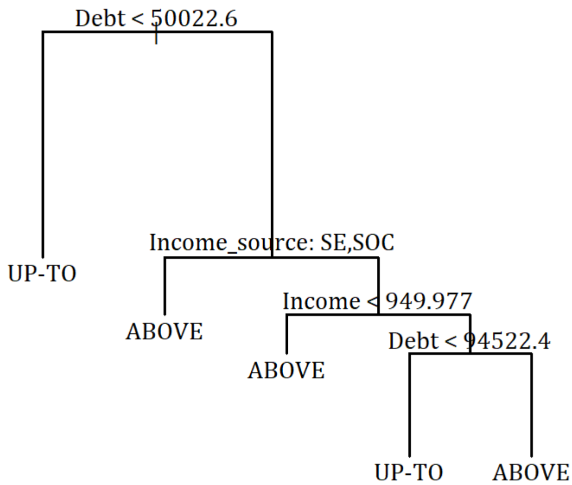
Distribution: UP-TO : ABOVE = 21488 : 3001
Missclassification error rate = 15.18 %
Balanced missclassification error rate = 12.78 %

2017– DTI limit = 8



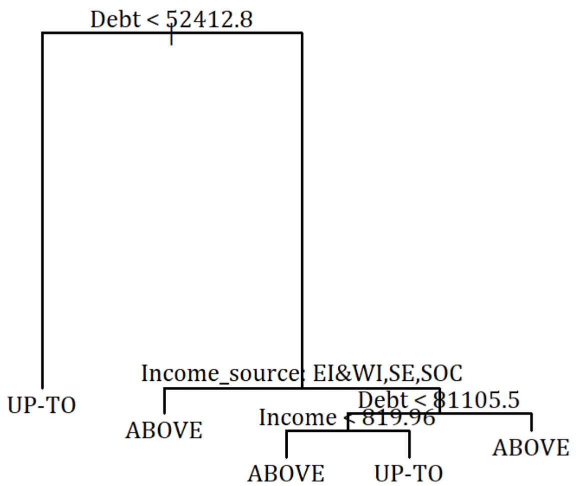
Distribution: UP-TO : ABOVE = 102605 : 4699
Missclassification error rate = 10.61 %
Balanced missclassification error rate = 6.57 %

2017 – DTI limit = 8 (Borrowers with housing loans)



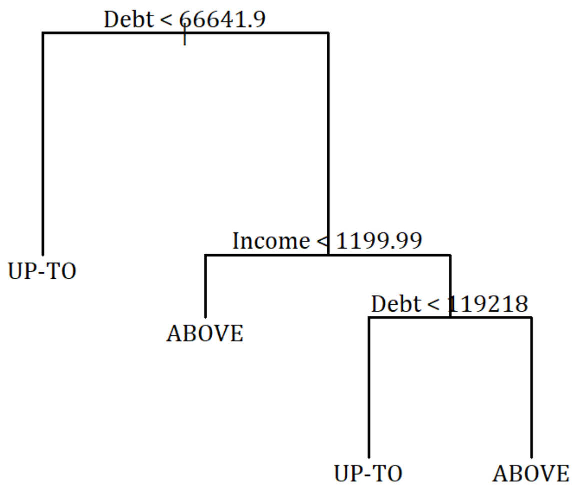
Distribution: UP-TO : ABOVE = 23628 : 3821
Missclassification error rate = 24.54 %
Balanced missclassification error rate = 15.33 %

2018– DTI limit = 8



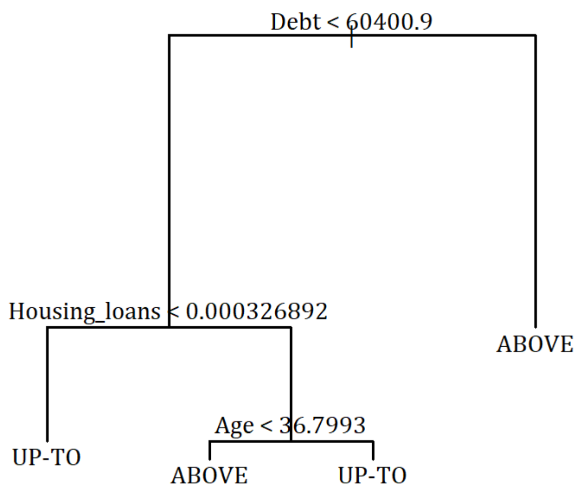
Distribution: UP-TO : ABOVE = 239735 : 7671
Missclassification error rate = 11.88 %
Balanced missclassification error rate = 8.27 %

2018 – DTI limit = 8 (Borrowers with housing loans)



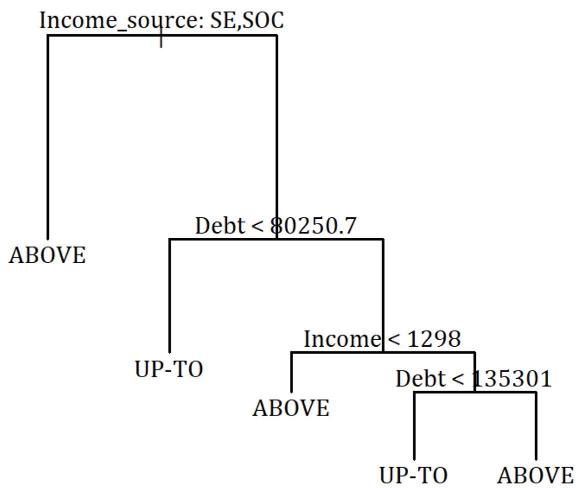
Distribution: UP-TO : ABOVE = 44420 : 5925
Missclassification error rate = 26.89 %
Balanced missclassification error rate = 19.32 %

2019 – DTI limit = 8



Distribution: UP-TO : ABOVE = 286948 : 4657
Missclassification error rate = 25.54 %
Balanced missclassification error rate = 14.51 %

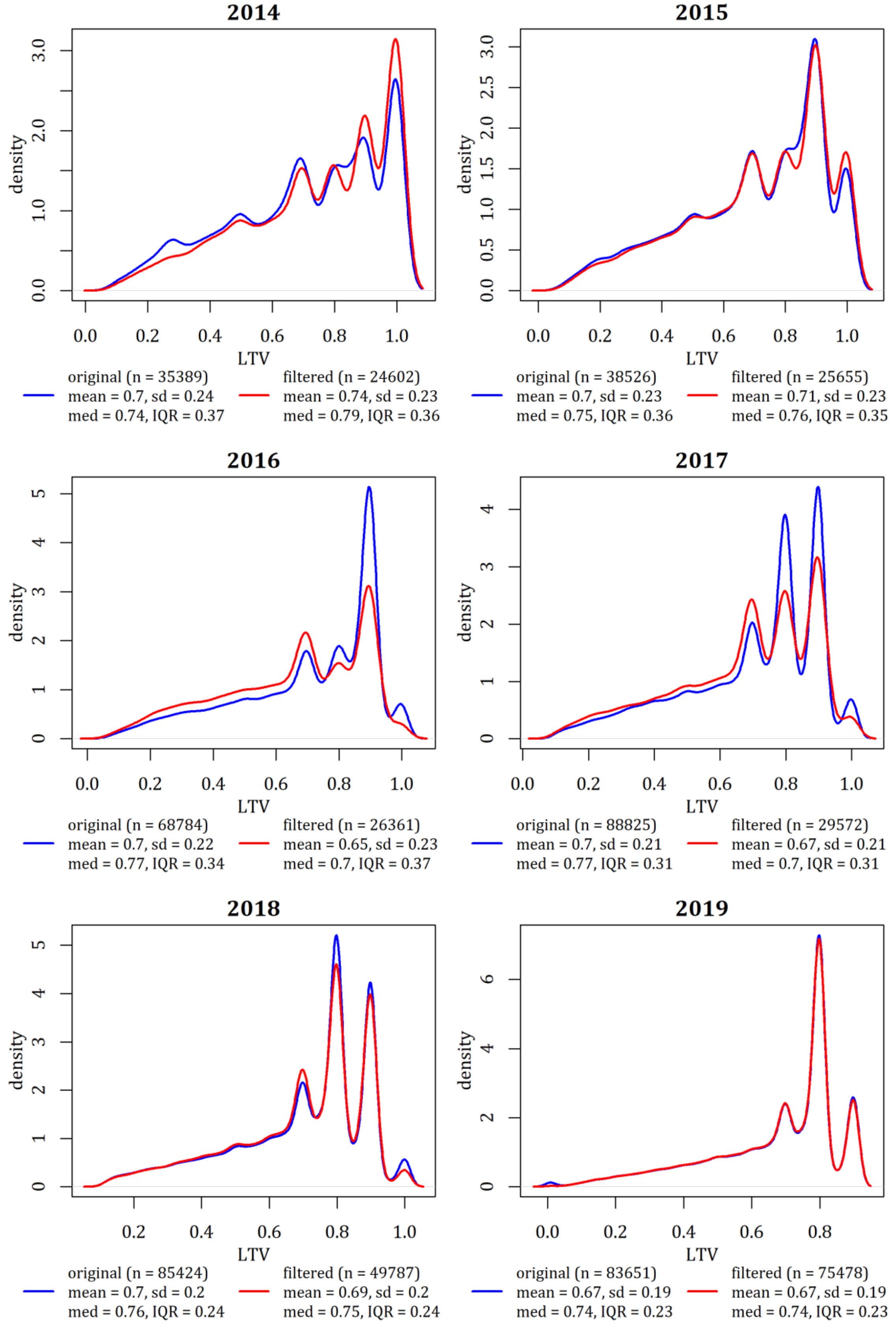
2019 – DTI limit = 8 (Borrowers with housing loan)



Distribution: UP-TO : ABOVE = 72392 : 3238
Missclassification error rate = 30.24 %
Balanced missclassification error rate = 29.6 %

Note: Housing_loans < 1 means, that borrower doesn't have a housing loan.

Appendix 8 Newly granted loans – distribution based on LTV



Note: original data = raw data with outliers cleared and missing values, filtered data = data filtered from original data, used in regressions and decision trees. Distributions were smoothed using the Kernel method, bandwidth parameter chosen based on the Silverman rule for each selection.

Appendix 9 Logit regressions – LTV

	$(1) Y = \begin{cases} 0; LTV \le 0.9 \\ 1; LTV > 0.9 \end{cases}$				$(2) Y = \begin{cases} 0; LTV \in (0.8, 0.9\rangle \\ 1; LTV > 0.9 \end{cases}$			
	2014		2015		2016		2017	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-7.45***	-0.347	-4.643***	-1.058	-7.214***	-1.728	-10.966***	-7.449***
	(0.459)	(0.665)	(0.512)	(0.651)	(0.859)	(0.998)	(0.81)	(0.931)
Reference category: SE								
Education = PE	-0.419	-1.205**	-0.983	-0.907	0.419	0.591	-0.803	-0.774
	(0.374)	(0.394)	(0.609)	(0.644)	(0.614)	(0.66)	(1.018)	(1.035)
Education = TE	-0.065	0.201***	-0.009	0.102*	0.306***	0.42***	0.225***	0.309***
	(0.034)	(0.044)	(0.039)	(0.045)	(0.07)	(0.074)	(0.068)	(0.073)
Reference category: BA								
Region = TT	0.112	-0.298***	-0.043	-0.273***	-0.156	-0.331**	-0.431***	-0.55***
	(0.057)	(0.074)	(0.065)	(0.076)	(0.118)	(0.125)	(0.113)	(0.121)
Region = TN	0.236***	-0.193*	-0.018	-0.209*	-0.023	-0.209	-0.449***	-0.619***
	(0.06)	(0.08)	(0.07)	(0.082)	(0.126)	(0.136)	(0.125)	(0.134)
Region = NR	0.406***	-0.253**	0.166*	-0.144	-0.117	-0.453***	-0.653***	-0.897***
	(0.06)	(0.078)	(0.069)	(0.082)	(0.127)	(0.135)	(0.133)	(0.142)
Region = ZA	-0.005	-0.239**	-0.297***	-0.292***	-0.221	-0.244	-0.538***	-0.484***
	(0.06)	(0.079)	(0.071)	(0.083)	(0.121)	(0.129)	(0.12)	(0.129)
Region = BB	0.338***	-0.2*	0.288***	-0.069	-0.157	-0.576***	0.13	-0.173
	(0.062)	(0.082)	(0.068)	(0.081)	(0.133)	(0.144)	(0.11)	(0.122)
Region = PO	0.153*	-0.245**	-0.122	-0.23*	-0.064	-0.263	-0.433**	-0.534***
	(0.065)	(0.087)	(0.076)	(0.09)	(0.134)	(0.144)	(0.134)	(0.143)
Region = KE	0.28***	-0.08	0.289***	0.006	-0.016	-0.363**	-0.189	-0.358**
	(0.058)	(0.078)	(0.066)	(0.078)	(0.118)	(0.126)	(0.112)	(0.121)
Age	-0.065***	-0.025***	-0.099***	-0.054***	-0.096***	-0.052***	-0.093***	-0.058***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)
Reference category: EM								
Income_source = SE	-0.584***	-0.475***	-0.507***	-0.24**	-0.627***	-0.407*	-0.949***	-0.849***
	(0.057)	(0.071)	(0.071)	(0.082)	(0.155)	(0.161)	(0.172)	(0.178)
Income_source = SOC	0.001	0.02	0.051	-0.007	-1.558**	-1.674**	-0.375	-0.292
	(0.121)	(0.155)	(0.132)	(0.15)	(0.583)	(0.587)	(0.346)	(0.358)
Income_source = EI&WI	-0.408	-0.402	0.132	0.146	-10.864	-11.482	-8.136	-
	(0.636)	(0.771)	(0.804)	(1.01)	(141.641)	(229.628)	(196.968)	-
Income (log10)	-0.725***	0.261	-0.495***	0.215	0.211	0.703**	0.891***	1.567***
	(0.105)	(0.141)	(0.129)	(0.158)	(0.236)	(0.261)	(0.228)	(0.272)
Instalments (log10)	0.029	-0.178	0.389*	-0.268	-0.675**	-0.469	-0.104	-0.165
	(0.161)	(0.226)	(0.156)	(0.189)	(0.224)	(0.24)	(0.196)	(0.199)
Debt (log10)	2.255***	0.252	1.414***	0.457*	1.913***	0.253	2.056***	0.95***
	(0.141)	(0.206)	(0.142)	(0.183)	(0.212)	(0.253)	(0.2)	(0.228)
Borrowers	0.032	0.094*	0.053	0.225***	-0.494***	-0.324***	-0.871***	-0.835***
	(0.036)	(0.045)	(0.04)	(0.047)	(0.074)	(0.077)	(0.075)	(0.082)
Pseudo R^2	0.1	0.02	0.11	0.03	0.1	0.04	0.13	0.08
Number of observations	24,602	10,947	25,655	10,394	26,361	8,097	29,572	8,335

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

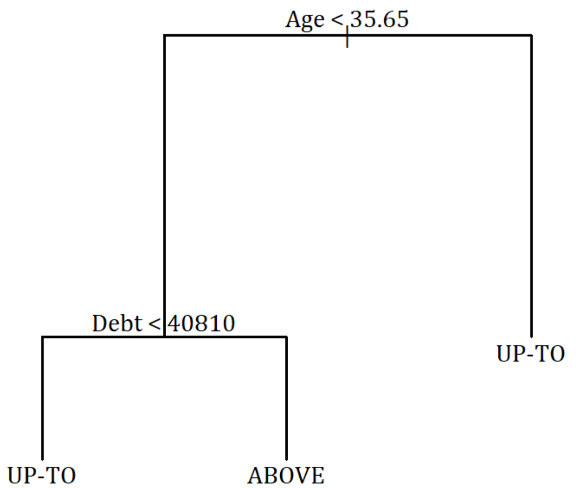
	$(1)\ Y=\begin{cases}0; LTV \le 0.8\\ 1; LTV > 0.8\end{cases}$	$(2)\ Y=\begin{cases}0; LTV \in (0.7, 0.8\rangle\\ 1; LTV > 0.8\end{cases}$						
	2016		**2017**		**2018**		**2019**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-8.059***	0.921	-7.284***	0.339	-4.791***	1.545***	-0.13	2.229***
	(0.375)	(0.559)	(0.34)	(0.443)	(0.272)	(0.327)	(0.2)	(0.22)
Reference category: SE								
Education = PE	-0.299	-0.781*	0.127	-0.145	0.477*	0.222	-0.952**	-1.055**
	(0.324)	(0.377)	(0.264)	(0.31)	(0.21)	(0.236)	(0.33)	(0.339)
Education = TE	-0.219***	-0.015	-0.181***	0.024	-0.091***	0.032	0.159***	0.254***
	(0.032)	(0.047)	(0.031)	(0.039)	(0.023)	(0.027)	(0.024)	(0.026)
Reference category: BA								
Region = TT	0.288***	0.008	0.174**	-0.087	-0.043	-0.221***	-0.395***	-0.493***
	(0.057)	(0.084)	(0.054)	(0.07)	(0.038)	(0.044)	(0.038)	(0.041)
Region = TN	0.355***	0.027	0.321***	-0.038	0.044	-0.193***	-0.501***	-0.577***
	(0.06)	(0.089)	(0.056)	(0.072)	(0.041)	(0.049)	(0.042)	(0.045)
Region = NR	0.574***	-0.013	0.418***	-0.073	0.084*	-0.265***	-0.541***	-0.722***
	(0.058)	(0.085)	(0.055)	(0.071)	(0.04)	(0.046)	(0.041)	(0.043)
Region = ZA	0.076	-0.078	-0.011	-0.243***	-0.215***	-0.297***	-0.801***	-0.741***
	(0.057)	(0.085)	(0.054)	(0.071)	(0.041)	(0.049)	(0.044)	(0.047)
Region = BB	0.73***	0.101	0.652***	0.033	0.276***	-0.134**	-0.435***	-0.618***
	(0.06)	(0.088)	(0.056)	(0.072)	(0.043)	(0.05)	(0.044)	(0.047)
Region = PO	0.416***	-0.014	0.306***	-0.062	-0.234***	-0.471***	-0.841***	-0.923***
	(0.061)	(0.09)	(0.057)	(0.075)	(0.045)	(0.053)	(0.049)	(0.052)
Region = KE	0.627***	0.179*	0.35***	-0.096	0.12**	-0.15**	-0.497***	-0.636***
	(0.056)	(0.085)	(0.054)	(0.07)	(0.039)	(0.047)	(0.039)	(0.042)
Age	-0.065***	-0.047***	-0.054***	-0.035***	-0.054***	-0.034***	-0.098***	-0.071***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Reference category: EM								
Income_source = SE	-0.458***	-0.258**	-0.312***	-0.13*	-0.169***	-0.024	-0.264***	-0.191***
	(0.056)	(0.079)	(0.052)	(0.065)	(0.038)	(0.043)	(0.041)	(0.043)
Income_source = SOC	0.2*	0.304*	0.095	0.153	-0.625***	-0.664***	-0.617***	-0.648***
	(0.099)	(0.146)	(0.102)	(0.131)	(0.081)	(0.088)	(0.09)	(0.093)
Income_source = EI&WI	-0.44	10.052	-8.359	-	-0.65	-0.615	-1.251**	-1.066*
	(0.952)	(139.277)	(72.463)	-	(0.395)	(0.438)	(0.464)	(0.476)
Income (log10)	-0.596***	-0.463**	-0.36***	-0.34**	-0.987***	-1.252***	0.898***	0.255***
	(0.103)	(0.152)	(0.099)	(0.128)	(0.077)	(0.089)	(0.066)	(0.073)
Instalments (log10)	-0.195*	0.464***	0.212*	0.779***	1.087***	1.484***	0.992***	1.067***
	(0.099)	(0.134)	(0.085)	(0.098)	(0.079)	(0.089)	(0.065)	(0.072)
Debt (log10)	2.573***	0.388**	1.919***	0.093	1.298***	-0.052	-0.59***	-0.796***
	(0.091)	(0.133)	(0.079)	(0.101)	(0.072)	(0.087)	(0.038)	(0.043)
Borrowers	-0.337***	-0.025	-0.319***	-0.076	-0.293***	-0.074**	-0.398***	-0.23***
	(0.033)	(0.047)	(0.032)	(0.04)	(0.024)	(0.027)	(0.025)	(0.026)
Pseudo R^2	0.13	0.03	0.09	0.02	0.08	0.03	0.09	0.06
Number of observations	26,361	11,463	29,572	14,245	49,787	27,456	75,478	41,021

Note: * p < 0.10; ** p < 0.05; *** p < 0.01. Standard errors in parenthesis.

Appendix 10 Decision trees – LTV

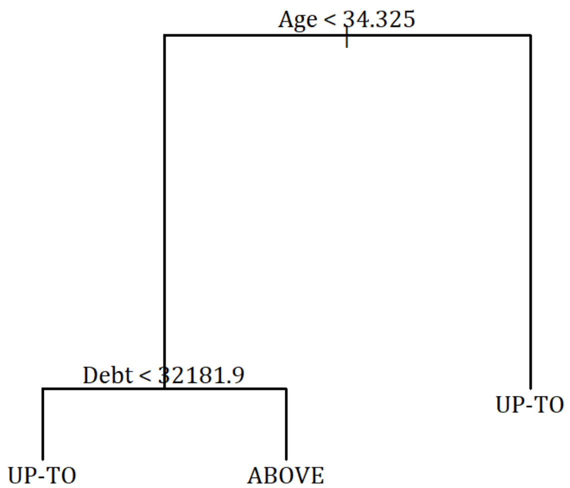
Oversampling using minority sample replication method

2014 – LTV limit = 90%



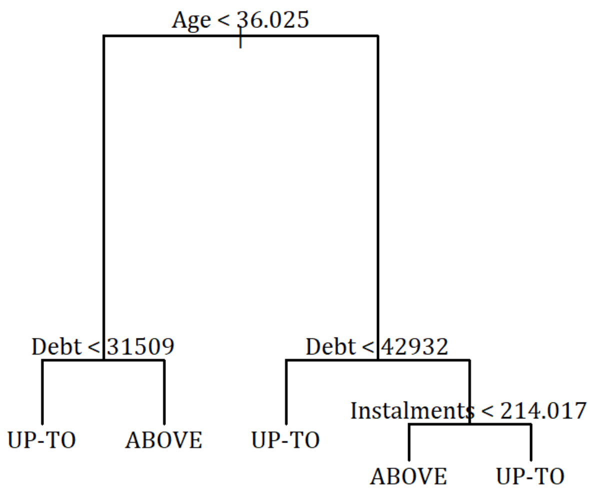
Distribution: UP-TO : ABOVE = 18148 : 6454
Missclassification error rate = 32.48 %
Balanced missclassification error rate = 33.87 %

2015 – LTV limit = 90%



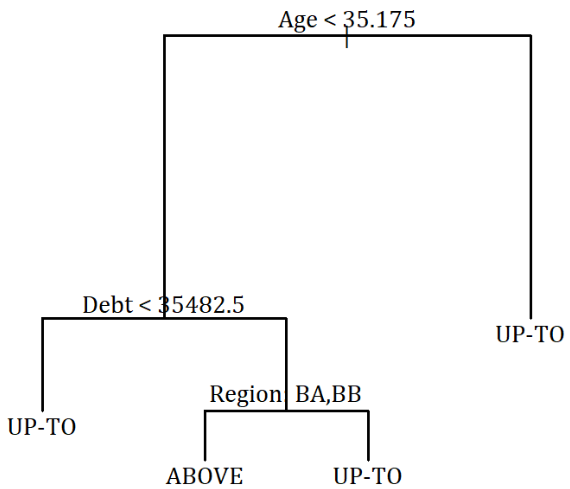
Distribution: UP-TO : ABOVE = 21500 : 4155
Missclassification error rate = 36.22 %
Balanced missclassification error rate = 32.12 %

2016 – LTV limit = 90%



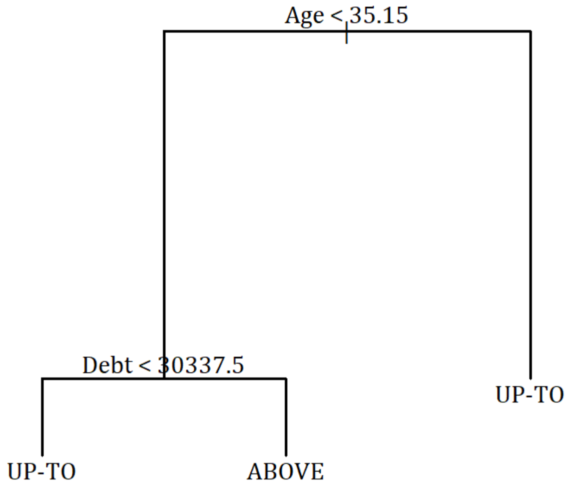
Distribution: UP-TO : ABOVE = 25345 : 1016
Missclassification error rate = 39.04 %
Balanced missclassification error rate = 29.23 %

2017 – LTV limit = 90%



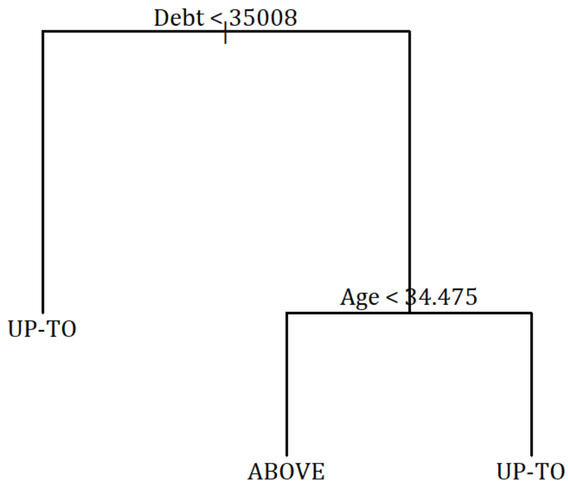
Distribution: UP-TO : ABOVE = 28478 : 1094
Missclassification error rate = 11.65 %
Balanced missclassification error rate = 38.22 %

2016 – LTV limit = 80%



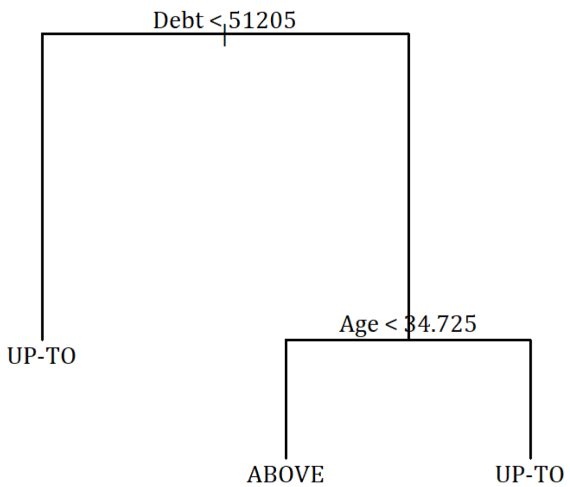
Distribution: UP-TO : ABOVE = 18264 : 8097
Missclassification error rate = 32.16 %
Balanced missclassification error rate = 34.35 %

2017 – LTV limit = 80%



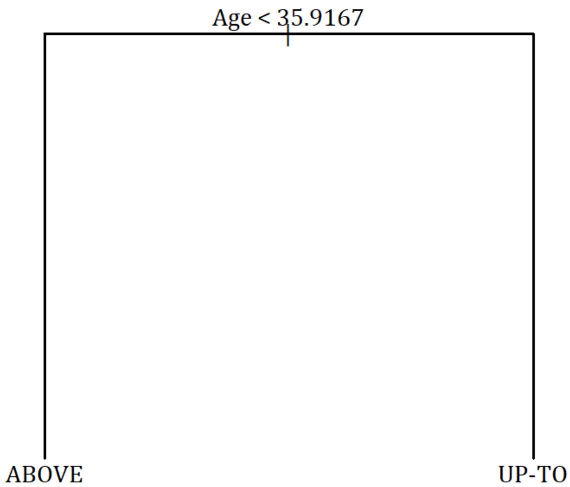
Distribution: UP-TO : ABOVE = 21237 : 8335
Missclassification error rate = 33.63 %
Balanced missclassification error rate = 36.65 %

2018 – LTV limit = 80%



Distribution: UP-TO : ABOVE = 37045 : 12742
Missclassification error rate = 34.42 %
Balanced missclassification error rate = 38.65 %

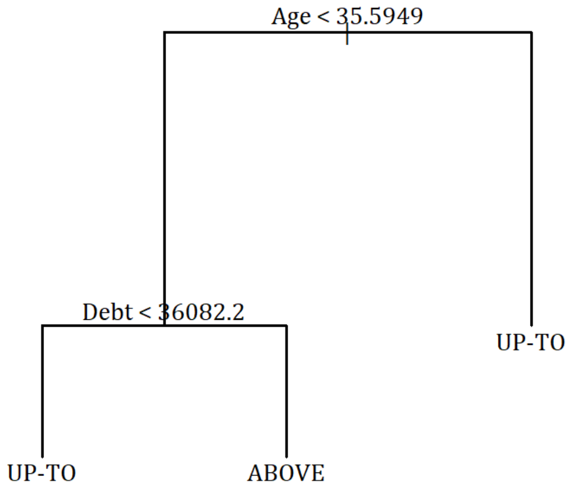
2019 – LTV limit = 80%



Distribution: UP-TO : ABOVE = 65538 : 9940
Missclassification error rate = 45.14 %
Balanced missclassification error rate = 37.04 %

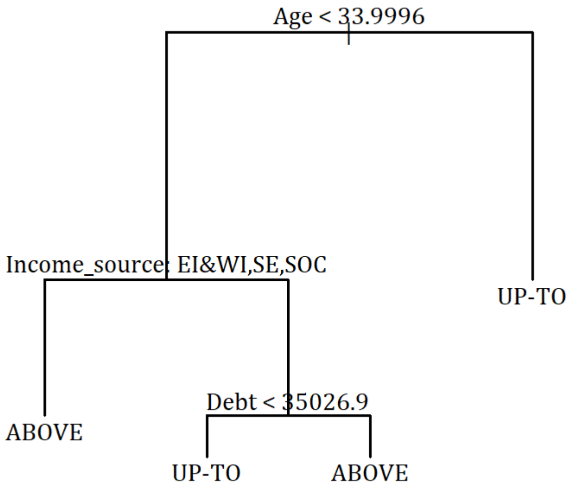
Oversampling and undersampling using SMOTE method

2014 – LTV limit = 90%



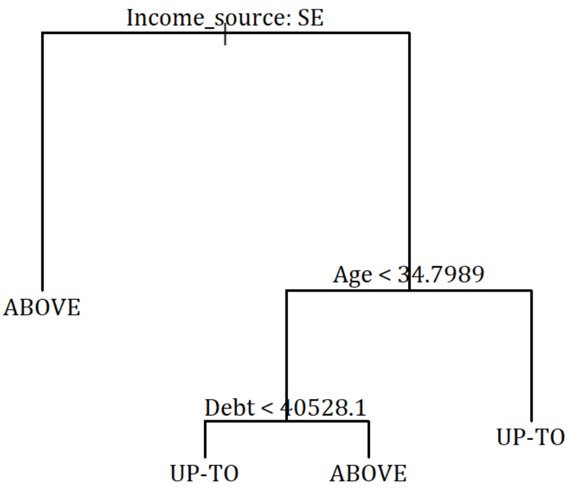
Distribution: UP-TO : ABOVE = 18148 : 6454
Missclassification error rate = 34.42 %
Balanced missclassification error rate = 33.66 %

2015 – LTV limit = 90%



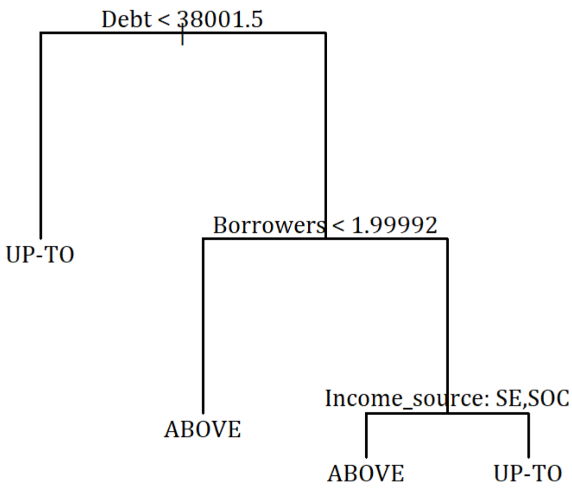
Distribution: UP-TO : ABOVE = 21500 : 4155
Missclassification error rate = 35.32 %
Balanced missclassification error rate = 33.01 %

2016 – LTV limit = 90%

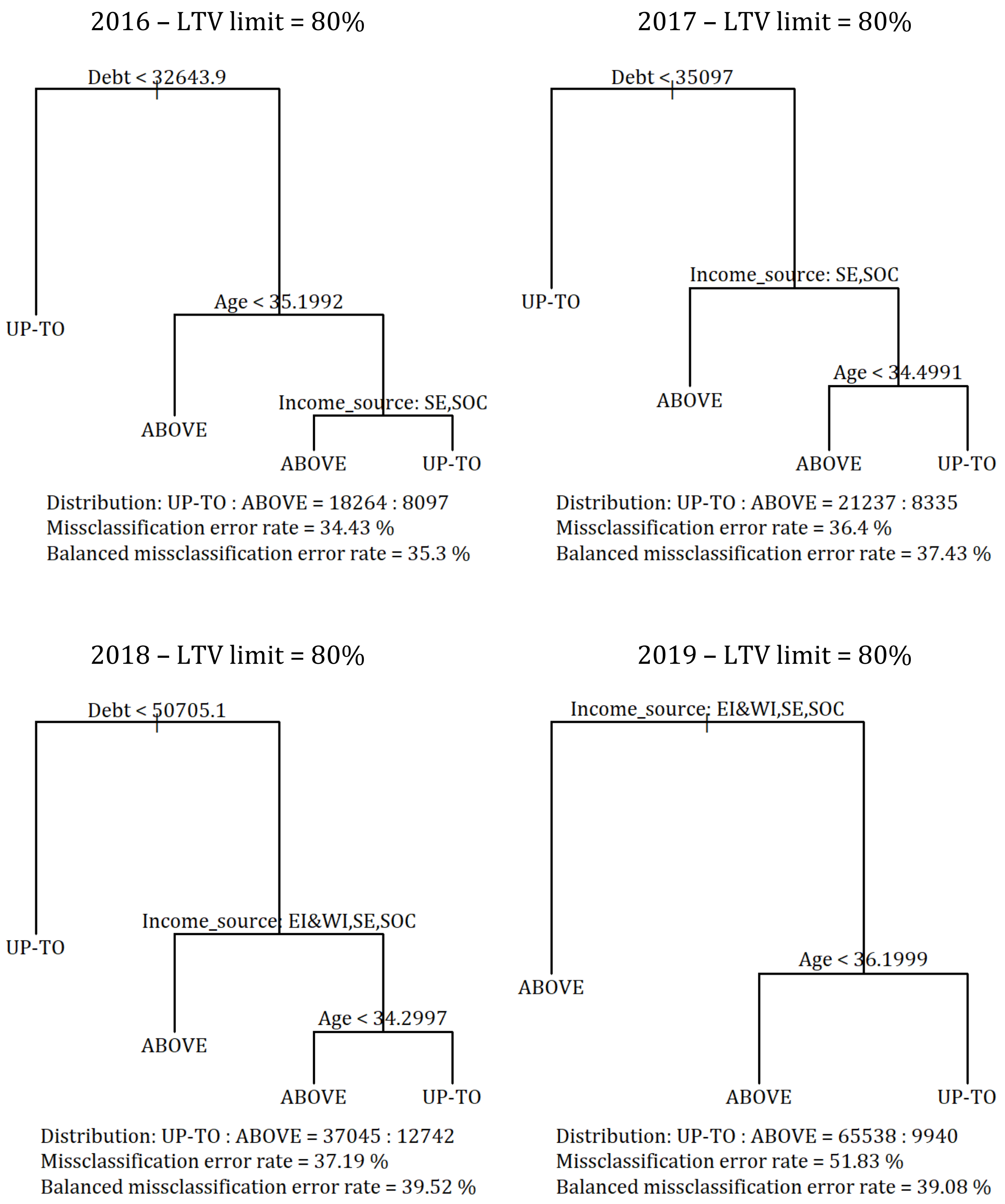


Distribution: UP-TO : ABOVE = 25345 : 1016
Missclassification error rate = 36.25 %
Balanced missclassification error rate = 33.87 %

2017 – LTV limit = 90%



Distribution: UP-TO : ABOVE = 28478 : 1094
Missclassification error rate = 35.37 %
Balanced missclassification error rate = 36.6 %



Note: Borrowers < 2 means single borrower.

Appendix 11 Scenarios for loan availability

		Annual income change	Annual change of interest rates on housing loans
Baseline scenario	2020	5.7%	+0 p. p.
	2021	5.0%	+0 p. p.
	2022	4.6%	+0 p. p.
Scenario 1	2020	-2.5%	+1 p. p.
	2021	8.3%	+0 p. p.
	2022	6.4%	+0 p. p.
Scenario 2	2020	-3.4%	+1 p. p.
	2021	8.3%	+0 p. p.
	2022	6.1%	+0 p. p.
Scenario 3	2020	-5.3%	+1 p. p.
	2021	8.8%	+0 p. p.
	2022	6.1%	+0 p. p.

Appendix 12 Estimated specification of error-correction models for the analysis of real estate prices

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5	Specification 6	Specification 7
Cointegrating equation							
ln(housing loans)	-0.061	-0.187	-0.186	-0.025	-0.149	-0.201	-0.216
ln(unemployment)	0.497			0.545			
Unemployment gap					0.142		
Intercept	-8.982	-4.529	-4.546	-9.704	-5.044	-4.347	-4.159
Adjustment coefficient							
α	-0.200	-0.116	-0.112	-0.188	-0.165	-0.144	-0.144
aR^2	70.7%	62.9%	63.0%	69.9%	58.0%	53.9%	53.0%

Note: specifications differ in variables included in the cointegrating equation as well as exogenous variables