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Micro-assessment of macroprudential borrower-based measures in Lithuania

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ABSTRACT

The high-paced growth of the Lithuanian mortgage market may cast doubt on either the efficacy of the country's macroprudential toolkit, or the appropriateness of its current parametrisation in putting a backstop to excessive dynamics. This paper assesses the adequacy of BBM's in Lithuania by building a novel lifetime expected credit loss framework that is founded on actual loan-level default and household income data. Based on the modelling framework we document seven findings which are relevant for policymakers. We show that the BBM package effectively contains mortgage credit risk and that housing loans are more resilient to stress than in the pre-regulatory era. Our BBM limit calibration exercise reveals that: i) in the low-interest rate environment income-based measures could have been tighter; ii) borrowers taking out secondary mortgages rightly are and should be required to pledge a higher down payment of at least 30%.

Keywords: macroprudential policy, borrower-based measures, LTV, mortgage credit risk, lifetime expected credit loss, probability of default.

JEL: C25, E61, G18, G21, G51.

Executive summary

Although macroprudential policy has been in place for more than a decade, Lithuania is yet again experiencing one the highest growth rates in home prices and mortgage lending in the Euro area, which are contributing to the rapid formation of financial imbalances. While macroprudential policy's primary objective is to strengthen resilience, it is also known that the toolkit can act countercyclically. The recent dynamism in the mortgage market casts doubt on either the efficacy of the country's macroprudential toolkit, or the appropriateness of its parametrisation in putting a backstop to excessive credit and credit-induced house price growth which happened in the low-rate period.

This paper assesses the adequacy of BBM's in Lithuania by building a novel lifetime expected credit loss framework that is founded on actual loan-level default and household income data. Based on the modelling framework we document seven findings which are relevant for policymakers.

Finding 1 Had current BBM limits been imposed preceding the GFC, the credit risk of housing loans would have been significantly lower, and aggregate mortgage losses at least 83% smaller than those experienced by Lithuania's banking sector during the crisis.

Finding 2 Over the last decade mortgage quality increased and borrowers are more resilient to adverse shocks compared to the pre-GFC period, at least partly due to the introduction of BBM regulations.

Finding 3 Effective containment of the probability of mortgage default can be achieved using income-based measures, especially the headline DSTI cap, whereby the LTV measure is more suitable at controlling the loss given default parameter.

Finding 4 The nonlinear relationship between the DSTI ratio and probability of mortgage default suggests that in the low-interest rate environment existing DSTI limits were loose, especially the stressed DSTI cap.

Finding 5 Since longer maturity loans may, *ceteris paribus*, have a higher chance of defaulting at least once during their lifespans, minimisation of lifetime credit risk while achieving a desired policy impact can be accomplished through a joint reduction in both DSTI and maturity limits.

Finding 6 Secondary mortgages: a) are more likely to default over their lifetime compared to an otherwise equivalent but single mortgage loan; b) impose a negative externality in terms of heightened default rate on the existing housing loan portfolio.

Finding 7 To compensate for high probability of default of secondary mortgages, their regulatory LTV limit rightly is and should remain: a) strictly lower than the headline LTV limit; b) differentiated by the current LTV of borrowers' first mortgage.

While Findings 4-5 suggest a need to tighten the BBM limits in Lithuania, our analysis does not account for the ongoing sharp reversal of monetary policy stance. Early data shows that the rapid rise in interest rates may be slowing down the pace of credit, possibly containing further accumulation of imbalances, rendering any rash macroprudential policy tightening unnecessary, if not harmful.

1 Introduction

Borrower-based measures (BBM) in Lithuania were adopted in 2011 as part of the macroprudential toolkit. The policy was supposed to address the harsh lessons of the past financial cycle which occurred in the 2000's and swept the country's economy into a deep recession during the Global Financial Crisis (GFC).[1]

In spite of having macroprudential policy tools in place for more than a decade, today's Lithuania is yet again experiencing one of the largest house price and mortgage lending growths in the Euro area (EA).[2] The situation brings on a *déjà vu* feeling and casts doubt on the macroprudential policy's ability to contain excessive credit and house price growth. Since empirical literature mostly suggests that BBM's can be effective in containing credit risk and smoothing credit cycles, one may question the appropriateness of the toolkit's parametrisation.

This is exactly the issue that this paper deals with. By using a rich household loan-level dataset spanning from 2004 to 2020 and containing information on family income and composition, we create an analytical framework that models the credit risk of each individual mortgage loan. The modelling setting allows us to understand how each mortgage's parameters that are restricted by BBM limits at loan's origination affect its successive lifetime performance, risk of default and expected loss.

Utilising the proposed setup, we inquire into Lithuania's BBM framework in three key areas: i) efficacy of measures; ii) appropriateness of current parametrisation; iii) additional regulation of secondary and subsequent mortgage loans.[3] Our analysis is based on two years worth of behind-the-scenes policy work and showcases how loan-level information could be utilised for policy evaluation. The paper documents seven findings which essentially support the effectiveness of BBM's in containing mortgage credit risk, and also suggest that an even more stringent regulation could be imposed. With regards to secondary mortgages, we show that their credit risk is higher than that of single mortgages, and thus support the recently passed regulation by the Bank of Lithuania, which imposes a higher down payment requirement for this particular asset class.

This paper contributes to the literature on macroprudential policymaking in at least three major dimensions. First and foremost, within a sparse strand of literature we develop an analytical framework that is based on actual loan-level default data and models the

[1]For references on Lithuania's experience and accumulation of imbalances preceding the 2009 crisis, see Ramanauskas (2005), Kulikauskas (2016) and Karmelavičius et al. (2022a,b). For coverage of the crisis period, refer to Kuodis and Ramanauskas (2009) and Ramanauskas (2011); and more recently Baudino et al. (2022) who analyse the events in the Baltic countries.

[2]Note that throughout this paper we will use the words *mortgage*, *mortgage loan*, *housing loan* or simply a *loan* interchangeably as synonyms and thereby refer to credit that is secured by residential real estate, unless specified otherwise.

[3]A mortgage loan is said to be secondary if during its inception the household has at least one other active housing loan.

credit risk of each individual mortgage. While many authors analyse the probability of default (PD) parameter, our PD model stands out from others with exceptionally high out-of-sample discriminatory power of around 90%. Additionally, we include the loss given default (LGD) parameter into our analysis to get a complete picture of credit risk by modelling the expected lifetime credit loss (ECL) – in the spirit of IFRS-9 requirements for accounting of loss allowances.

Secondly, our framework allows us to jointly analyse multiple BBM's and investigate their interactive impact on credit risk. We calibrate the macroprudential measure limits using micro-level data what has been done very rarely in the literature, with only few exemptions in Kelly and O'Toole (2018), Nier et al. (2019) and some others. Although there are some papers which investigate lifetime credit risk of mortgage loans (see Gaffney et al., 2014, and references therein), our paper is the only one in related literature that employs a lifetime framework for calibration of BBM limits.

While the literature on calibration of BBM's is scarce, the number of loan-level-based papers that study specific pockets of the market like buy-to-let investors or secondary mortgages is even rarer. As a third contribution, we dive into the investors' segment and investigate the credit risk of secondary mortgage loans. Our analysis is one of the very few to calibrate a loan-to-value (LTV) limit for secondary mortgages, with a notable exception of Kelly and O'Toole (2018) who analyse multi-loan borrowers.

The paper is structured as follows. Section 2 presents some background information on Lithuanian BBM framework and recent dynamics of the mortgage market. Section 3 develops the credit risk modelling framework which is utilised for the assessment of BBM's in Sections 4 and 5. Lastly, we conclude with some findings and a general discussion on the appropriateness of the policy setting.

2 Background information

In this section we provide some background information regarding the BBM's in Lithuania, recent dynamics of the mortgage market, and discuss some BBM policy alternatives.

2.1 Institutional set-up

In Lithuania, macroprudential policy is solely conducted by the central bank. Among macroprudential policy tools that are in the disposition of the Bank of Lithuania are BBM's, which were adopted in 2011 through the enactment of Responsible Lending Regulations (Lith. *Atsakingojo skolinimo nuostatai*, ASN hereafter).[4] Although the framework

[4]Links to an up-to-date ASN document for credit secured by real estate for natural persons: in Lithuanian, in English. In addition to ASN, housing loans are regulated by the Law on Real Estate Related Credit, enacted in 2016.

applies to all credit for natural persons that is secured by real estate, we will focus only on residential housing loans which comprise the majority of loans under the regulation.

The BBM's that are within the scope of the ASN regulation limit borrower's mortgage credit uptake through a requirement on down payment, a limit on loan maturity and monthly installments. Table 1 summarises ASN measures and their corresponding limits that are in place at the time of writing this paper. More specifically, the LTV requirement puts an 85% limit on the loan amount compared to the value of pledged real estate collateral. The latter limit implies a 15% minimal down payment requirement for a leveraged house purchase.[5]

Table 1: Current ASN limits for mortgages in Lithuania

Measure	LTV	LTV^2	DSTI	$DSTI^*$	Maturity
Limit	85%	70%	40%	50%	30 years
Applicable since	2011	2022	2011	2015	2015

Notes: LTV^2 denotes LTV limit for secondary mortgages, which came into effect on February 1, 2022. The 70% limit for LTV^2 is applied only for borrowers whose first mortgage current LTV stands above 50% at the inception of secondary mortgage. Credit institutions may use an exemption and apply a DSTI limit of 60% for creditworthy customers, however, the amount of loans issued with such exemptions shall not exceed 5% of the institution's annual mortgage flow. $DSTI^*$ denotes the stressed DSTI limit, which cannot be exceeded after applying a 5% interest rate sensitivity test.

As of February 1, 2022, the LTV limit was restricted to 70% for second and subsequent (LTV^2) mortgage loans with an exemption for borrowers, whose first mortgage current LTV is lower than 50% at the time the secondary mortgage is initiated.[6] The more stringent $LTV^2 \leq 70\%$ requirement was imposed to limit leveraged investments that are putting additional strain on the housing market, and to equalise the credit risk between single-mortgage and multiple-mortgage debtors. A thorough discussion of this credit market segment is presented later in this section, and the calibration of the LTV^2 limit is covered in Section 5.

While the cap on LTV can be viewed as a solvency requirement that is related to borrower's equity or own-funds, the debt-service-to-income (DSTI) limit is more of a liquidity measure. Essentially, the DSTI requirement imposes a 40% limit on average monthly loan payments, i.e. instalments and interest payments, as a share of borrower's monthly disposable income. To safeguard borrowers from taking up excessive debt during the low-rate period and increase their resilience to possible future interest rate shocks, Bank of Lithuania imposed an additional sensitivity $DSTI^* \leq 50\%$ limit, where $DSTI^*$ is computed with mortgage interest rate of 5%. Given the fact that almost all mortgage loans in Lithuania are granted with variable rates, such measure mitigates the impact of

[5]Very importantly, ASN framework disallows the use of borrowed funds for down payment, implying that the borrowing party must take time and effort to save up for a mortgaged house purchase. In principle, such requirement should decrease and smooth credit demand over the course of the financial cycle, potentially reducing the probability of high asset price growth.

[6]See announcement news.

interest rate rises, especially for loans that were initiated in the low-rate environment.

The 30 years loan maturity limit that was introduced in 2015 serves two functions.[7] Firstly, when combined with the DSTI requirement, together they limit borrower's indebtedness as a share of income, i.e. debt-to-income (DTI). Secondly, a ceiling on the duration of a credit agreement enhances consumer protection by requiring at least some amount of amortisation, disallowing perpetual interest payments, thus lowering the cumulative amount of interest paid by the borrower.

2.2 Effectiveness of BBM's

In general, BBM's are primarily used for two main macroprudential purposes. First and foremost, they enhance the resilience of households and credit institutions to aggregate shocks to income, unemployment and interest rates, as well as swings in asset prices. For instance, on the basis of an integrated household-macro model of Gross and Población (2017), authors find that LTV and DSTI requirements significantly reduce household credit risk and associated banking sector losses (see Jurča et al., 2020; Ampudia et al., 2021; Neugebauer et al., 2021).

Second, BBM's act countercyclically by smoothing credit demand over the course of the financial cycle, potentially reducing the probability of high asset price growth and accumulation of imbalances. This channel is supported by numerous empirical papers, including Lim et al. (2011), Cerutti et al. (2017), Alam et al. (2019), Poghosyan (2019), and meta analyses of Araujo et al. (2020) and Malovaná et al. (2022).

Ultimately, macroprudential policy can reduce tail risks to GDP growth, although at a short-term loss in economic activity (for assessment of costs, see Richter et al., 2019). Using a cost-benefit framework and data on 37 countries, Brandao-Marques et al. (2020) find that macroprudential tools, and BBM's in particular, can be net-beneficial, i.e. they significantly reduce longer-term tail risks to GDP growth with relatively limited short-run losses.

The effectiveness of the ASN framework in Lithuania has been studied in only a few papers, primarily concerned with the impact of the LTV requirement. Most notable is that of Reichenbachas (2020) who finds that the imposition of the LTV limit acted countercyclically. The author empirically estimates that if the LTV requirement had not been introduced in 2011, household loan portfolio would have grown on average 1.5 p.p. faster (over 2012-2014), leading to a 0.5 p.p. higher average house price growth. Furthermore, if the LTV limit had been implemented in the 2000's, it would have substantially helped in tempering the credit and housing boom.

In addition, Rutkauskas et al. (2015, p. 72) stress-tested Lithuanian household credit portfolio using loan-level data and found the portfolio to be resilient to adverse scenarios.

[7]See announcement news.

The authors concluded that the ASN framework, in particular DSTI and LTV requirements, increased the shock absorption capacity of household loans. Complementing this, Matkėnaitė et al. (2016) showed that if the LTV requirement had been present preceding the crisis of 2009, it would have significantly boosted banking sector's resilience to a house price correction – mortgage credit losses would have been 83% smaller than the ones experienced in 2009.

Using a DSGE model that is calibrated to Lithuanian data, Karmelavičius (2021) finds that a tightening of the LTV requirement may act countercyclically by lowering both credit and house price growth, and also increase resilience by reducing the mortgage delinquency rate. More specifically, a 1 p.p. tightening of the LTV limit decreases mortgage portfolio by -0.5% and house prices by -0.15%, lowers mortgage default rate by -1.75 p.p., with impact on GDP being around -0.1%. Moreover, Rubio and Comunale (2016) calibrate a two-country DSGE model for Euro Area and Lithuania, and explore various Taylor-type rules for macroprudential policy, namely, the LTV limit. The authors find that it is optimal to countercyclically change the LTV limit in response to credit growth.

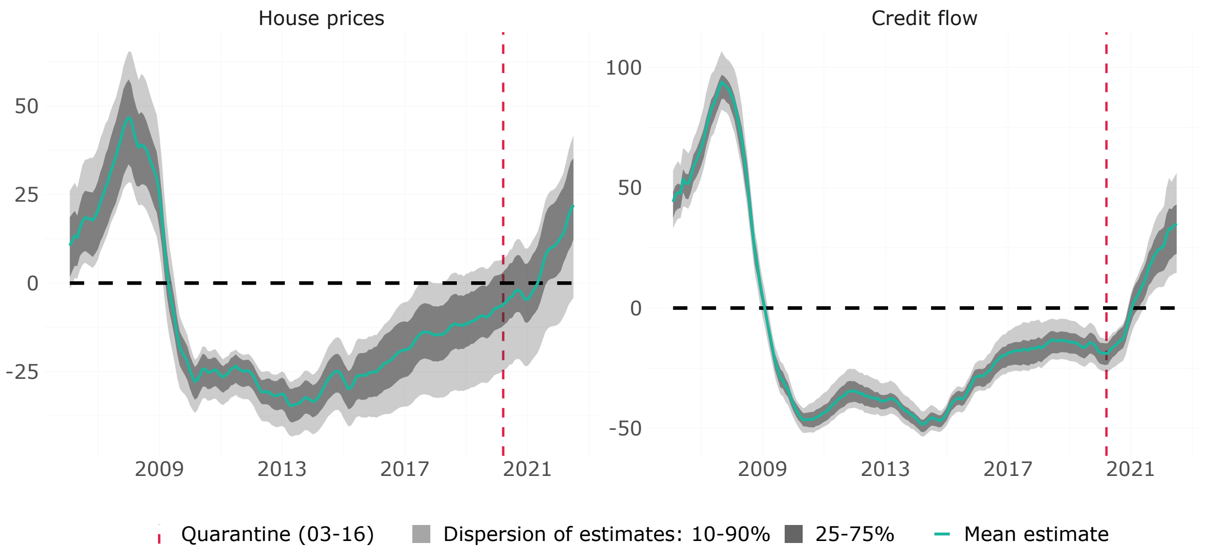
Besides the resilience and countercyclicality effects of BBM's, one has to acknowledge that there may be unintended social consequences of such regulation. Among others, Matkėnaitė et al. (2016) argue that excessively stringent LTV regulation may restrict households' access to housing and reduce home ownership. Financially constrained people, e.g. young families, would be forced to rent housing for prolonged periods of time, increasing rental demand and potentially inflicting a vicious rental cycle. Less financially constrained buyers, e.g. investors, may corner the housing market by purchasing housing units in bulks, thus raising both house prices and rental rates, and eventually wealth inequality.

The distributional channel of macroprudential policy has been explored by Acharya et al. (2022), who find that after the introduction of BBM's in Ireland, borrowing shifted from low-income to high-income households, and from urban to rural areas. Also, Tzur-Ilan (2020) shows that the introduction of LTV limits in Israel resulted in constrained borrowers purchasing lower quality housing and farther away from the city centre, with higher interest rates. The long-term side effects of BBM regulation in Lithuania remain to be seen, however, we can already observe that over the last decade since the inception of ASN, rental prices have accelerated and grown on average 1 p.p. higher than house prices on annual basis.

2.3 Mortgage market dynamics

Although ASN framework is present for more than a decade, Lithuania's housing market is one of the most dynamic in the EA. For the past two years, house prices and mortgage portfolio have been growing at a double-digit annual pace, with year-on-year growth rates peaking at 26.8% and 12.3%, respectively. The Covid-19 pandemic did little to slow down the housing market, whose growth has even accelerated and reached 15-year heights.

Figure 1: House price overvaluation and mortgage overflow



Note: measures of misalignments based on a two-market disequilibrium model of Karmelavičius et al. (2022b). The series are per cent deviations from fundamental values

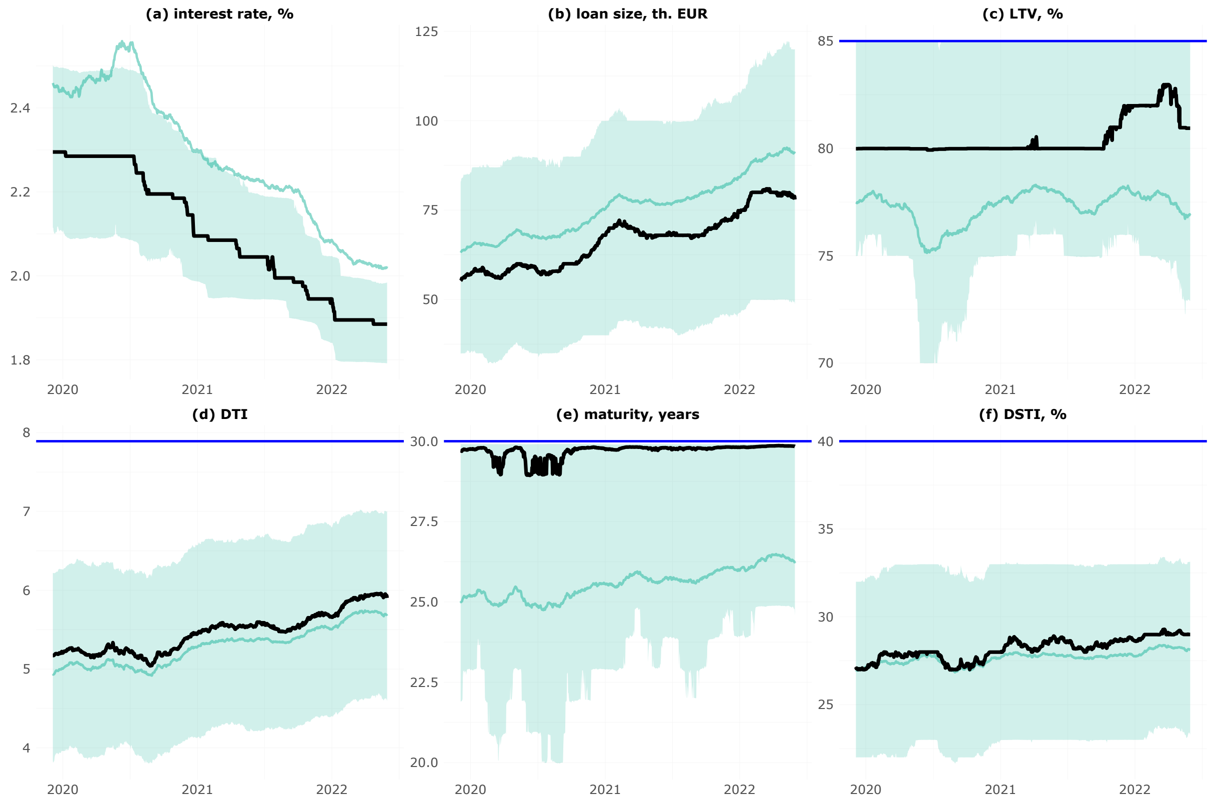
The elevation of heat is also indicated by different statistical models, including the two-market disequilibrium approach of Karmelavičius et al. (2022b) depicted in Figure 1. Measurements of misalignments suggest that home prices are 20% above their fundamentals, and that for the past year there has been a mortgage credit overflow of around 15%. It is important to note that if the current situation continues, current misalignments which are still modest by historical standards can lead to a rise in systemic vulnerabilities.[8].

The opening of the house price and credit gaps can be understood as both the cause and effect of deterioration in lending standards. We inspect this by taking a look at the recent aggregate trends of loan-level characteristics such as interest rates, loan size, LTV and other metrics which are depicted in Figure 2. One can observe that over the last two years, before the shift in monetary policy stance, there was a steep fall in mortgage rates for new lending. Not only the median rate went from 2.3% to 1.9%, but the rates became more compressed – less scattered around the median. This process coincided with more active participation of some banks in the credit market, suggesting of higher competition pressures.

Naturally, in response to increasing home prices, changes in housing preferences and reduction of interest rates, the average loan size increased from 60 to 90 th. EUR – a 40% increment over two years. As household disposable income growth lagged behind

[8]The current broad-based credit-to-GDP gap is still negative in Lithuania, however, the gap that is based on mortgage stock is closed, i.e. near zero. If the high flow of mortgage credit into the economy is sustained for a prolonged period of time, and the overflow gap depicted on the right-hand side of Figure 1, does not close, it can invoke a positive mortgage credit-to-GDP gap.

Figure 2: Rolling characteristics of new housing loans



Notes: 2-month rolling means (green line), medians (black line) and IQR's (green area) for new mortgage contracts, by date of inception. Horizontal blue lines mark the regulatory ASN limits. The data for mortgage interest rates coincides with mortgage margins, as data coverage is for period when Euribor was still negative and Euribor floor was applied. Data is sourced from the new PRDB database – credit register.

increasing home values, it became increasingly difficult to accumulate down payment, thus household indebtedness slightly increased in terms of median LTV and DTI ratios. Although housing loan size is rising faster than household income, DSTI measure remains remarkably stable – an effect of lower interest rate margins and somewhat longer maturities. Nonetheless, the burden of interest rate payments (DSTI) for variable-rate loans is already on the rise, and probably will remain, as the ECB continues to normalise monetary policy by increasing interest rates.

Secondary mortgages

What also emerged during the Covid-19 pandemic is the increase in prevalence of secondary mortgages, that is, households taking out second or third mortgages to finance additional house purchases, with their first mortgage still being active. Figure 3(a) shows that secondary mortgage share in new lending flow increased from 9.9% to 12.9% throughout 2019-2021. Looking at the regional level, we can see that this increase is common across all Lithuania, with biggest gains in coastal region of Klaipėda, Palanga and Neringa – a resort area. Historically, the share of secondary mortgages has been rather procyclical, tending to increase along with home prices and housing market activity, possibly amplifying the financial cycle. Therefore, the increased absolute volume and relative share of secondary mortgages is undesirable as the phenomenon may create financial stability issues.[9]

Customers taking out secondary housing loans are most likely buying houses that would not be their primary residences, and be used either for own-leisure purposes, e.g. in coastal resort areas, or for investment as buy-to-lets.[10] Taking this into account, it is very likely that the credit risk of a household with a secondary loan is greater compared to a household with a single mortgage, what primarily stems from two possible channels.[11]

The first and more obvious is the ability to pay, or liquidity, channel – for any household with more than one mortgage, it will be more difficult to service its debts. This is highlighted by panel (c) of Figure 3, where one can see that the DSTI distribution of secondary loans is heavily shifted rightwards. Households that have more than one mortgage will be more susceptible to changes in interest rates and loss of income, be it rental, labour or capital.

The second is the equity channel – a mortgage is more likely to default, as measured by the PD, and incur greater banking losses, as measured by the LGD, if the LTV ratio of that loan is high. Judging from Figure 3(c), we can observe that the LTV distribution of secondary mortgages is concentrated around 80% – more than half of loans have LTV's that are between 80 and 85% – deemed as relatively high.[12] Also, when looking at the data, we do not see any negative relationship between the LTV of a secondary mortgage and the borrower's first mortgage current LTV. Although natural person bankruptcy protection in Lithuania and the EU is quite weak – partial or full recourse systems, once housing value drops and the secondary mortgage becomes underwater, the debtor will be less likely to hold onto that non-primary residence and default, implying a higher PD parameter. What is more, in a full or partial recourse system, the LGD parameters of the first and secondary mortgages may be correlated, as the recovery would be sourced from the very same person's income or other assets that he owns. This creates an additional

[9]Nonetheless, secondary mortgages may create economic value for both individual borrowers and for the society as a whole. The latter stems from the fact that secondary mortgages are often used for financing the betterment, e.g. refurbishment, of existing housing units, which had been of low quality. Also, secondary mortgages may create value for lessees or tenants, increasing the supply in and quality of the rental market. Of course, one has to bear in mind that secondary mortgages are merely a means of financing an end – investment into housing, which can otherwise be acquired with own-funds.

[10]In some cases, customers switch their primary residence to the second house, and use their first house for rental services. It may also be possible that in some instances parents take out secondary mortgages and buy flats in urban areas, e.g. capital city Vilnius, for use by their children.

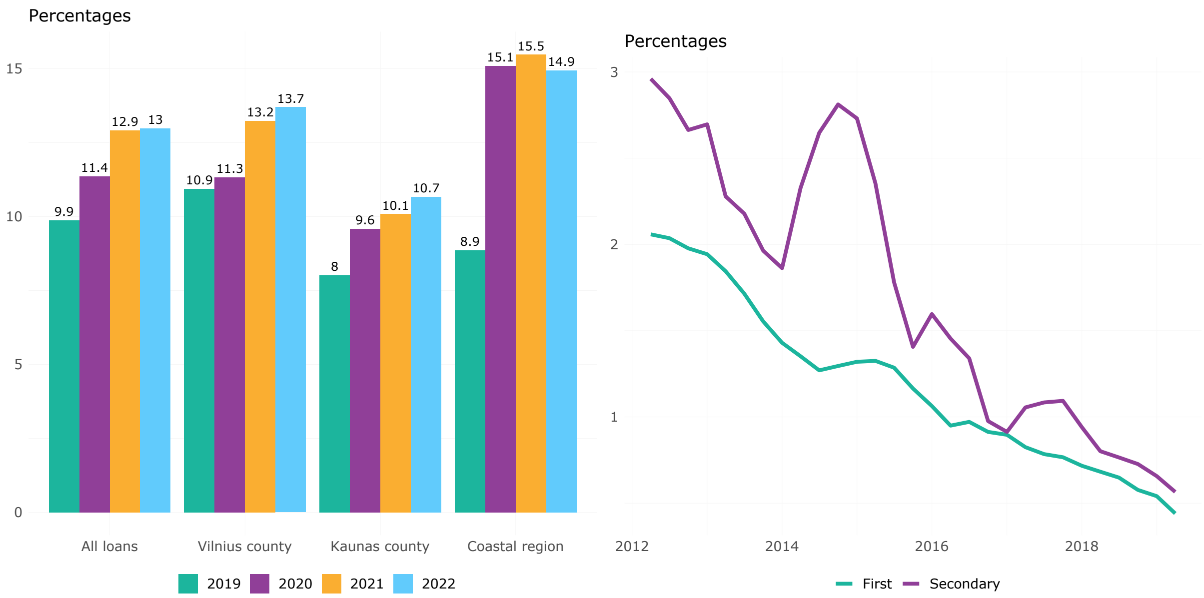
[11]Kukk (2021) signifies that there are two theories of why people default, namely, the "equity" theory and the "ability to pay" theory. The equity theory explains strategic default, which is mostly related to debtor's negative equity and relative value of collateral, i.e. the house. The ability to pay theory is mostly linked to the liquidity of a customer as measured by, say, the DSTI ratio. According to the author, equity theory is less relevant for European countries, since most of them exhibit full recourse systems.

[12]Under the regulation that was valid until 1 February 2022, strictly lower than 85% LTV limit for secondary mortgage loans was imposed.

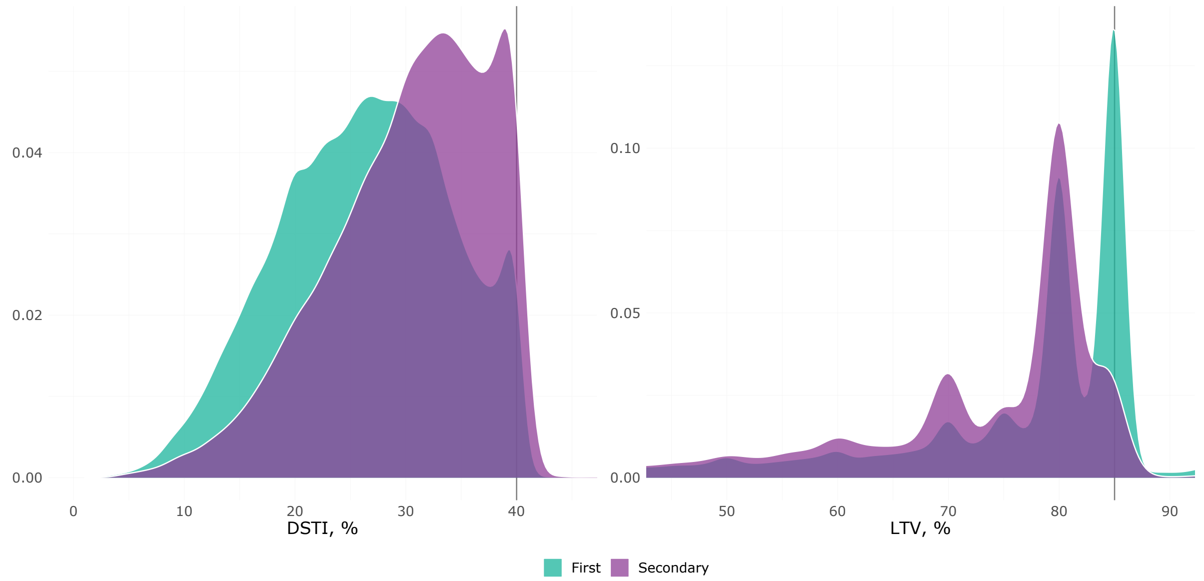
dimension of risk via the elevated LGD parameter.

Figure 3: Properties of secondary mortgages

(a) Share in new lending flow (b) Historical delinquency rate



(c) DSTI and LTV densities



Notes: a mortgage loan is said to be secondary, if during its inception the household has at least one other active housing loan. (a) Share of secondary mortgages from a total residential real estate credit flow. The geographical breakdown is related to the address of the collateral house. (b) Volume of housing loans that become non-performing (over 1-year horizon), divided by outstanding volume of all housing loans. (c) DSTI and LTV distributions at origination – for new mortgage contracts. Black vertical lines mark DSTI = 40% and LTV = 85% limits.

The idea that secondary mortgages do default more often is supported by our data, as can be seen from Lithuania's historical delinquency rate series in Figure 3(b). Throughout 2012-2020, while first mortgage average default rate was around 1%, secondary mortgage default rate was over 1.5% – a 50% higher chance of non-performance. This is also supported by other research papers, including that of Kelly and O'Toole (2018), who show that multi-loan borrowers have a higher default risk, even after controlling for DSTI ratio and other borrower-loan characteristics. Adding to this, Galán and Lamas (2019) find that mortgages on second-home properties have a higher PD. Furthermore, secondary mortgages are more risky, because, obviously, they are not taken out by first-time buyers, who are known to be low-risk borrowers, as found by Kelly et al. (2015), Mihai et al. (2018), Nier et al. (2019), among others. Lastly, Baptista et al. (2016), using an agent-based modelling setting, show that buy-to-let investors "may amplify house price cycles and increase house price volatility". Building on this evidence, in Section 5 we will show that on the basis of historical loan-level data in Lithuania, secondary mortgages indeed exhibit a higher likelihood of default, when controlling for loan and borrower features like DSTI, LTV, borrower's history, and others.

To complete our point on why secondary mortgages are undesirable, we lay an additional macroprudential argument to the above-discussed credit risk of microprudential nature. If prevalent, secondary mortgages add additional fuel to the housing market, contributing to existing home price and credit flow gaps. Given the elevated credit risk of second and subsequent housing loans, and their procyclicality, they may create negative externalities on significantly less riskier borrowers, such as first-time buyers, or other parts of the financial system. Furthermore, secondary mortgages may exacerbate the previously-mentioned side effects of macroprudential policy. By the act of acquiring additional housing units with secondary mortgages, borrowers inflate house prices and reduce the supply of housing-for-purchase, accelerating the vicious rental cycle of financially constrained households.

Observing the increasing prevalence of secondary mortgages and taking similar to the above-outlined arguments into account, Bank of Lithuania decided to strengthen the regulation of secondary mortgages by imposing a 70% LTV^2 limit, which came into effect on February 1, 2022 (see Table 1). This paper's Section 5 will shed light on the secondary mortgage LTV^2 limit assessment exercise that had been undertaken before the policy conclusion was reached.

2.4 Tightening options

Recent exuberance in the housing market and associated misalignments suggest that current macroprudential stance in Lithuania can be characterised as loose. While BBM's primarily boost the resilience of lenders and debtors, it is also desirable for the toolkit to work countercyclically and dampen the formation of imbalances. From the latter perspective, an opening of credit gaps, like the ones depicted in Figure 1, signals that the current regulatory ASN framework is not stringent enough.

On the other hand, Lithuanian BBM's are quite stringent, if compared to requirements in other European countries, as tabulated in Table 2. For example, the LTV limit of 85%

ranks as the 2-nd strictest, with many states having an LTV that is looser – 90, 95, or even a 100%. As income-based regulation is more diverse across different countries, we compare the effective DTI cap, which is based on the DSTI limit and maturity cap. In terms of the effective DTI requirement, Lithuania is once again amongst the jurisdictions with more stringent limits. Taking a look at the other two Baltic countries, which are of similar risk profile, namely Latvia and Estonia, we can see that Lithuania's LTV is the most restrictive, while the effective DTI is the least stringent of the three. However, when conducting a comparative analysis against other countries, one has to bear in mind that BBM frameworks across Europe are not necessarily optimal – in some cases the BBM limits are relatively loose, what may had been influenced by low affordability of housing in the past. And conversely, loose macroprudential stance may fail to dampen price growth, thus ultimately be a cause of unaffordable housing.

Table 2: Borrower-based measures in select European countries

Country	**LTV**	**DSTI**	**Maturity**	**LTI**	**DTI**	**Effective DTI**
Ireland	90			3.5		3.5***
Denmark	95			5		5***
Norway	85				5	5
Latvia	95	40	30		6	6
France		35	25			6.9
Estonia	90	50	30			6.9
Austria	80	30 (up to 40)	35			7.5
Lithuania	85	40 (up to 60)	30			7.8
Poland	90		25 (up to 35)			7.9
Slovakia	90	60 (up to 70)	30		8	8
Malta	90	40	40			8.6
Netherlands	100		30			9
Iceland	90	40				9
Czechia	90	45 (up to 50)	30			10
Romania	85	40				9
Slovenia	80	50 (up to 67)				11.3
Hungary	80	50 (up to 60)				11.3
Portugal	90	50 (up to 60)	40			13.8
Cyprus	80	80				18
Luxembourg	100					
Finland	95					
Sweden	85					
Liechtenstein	80					

Notes: this table was compiled and kindly provided by Mrs. Milda Stankuvienė, a Senior Economist of the Bank of Lithuania, on June 1, 2022. Please note that BBM frameworks are not harmonised across countries, with various peculiar qualitative features and exemptions, therefore one has to look at this table as only one of many possible representations.
LTV limit is the primary limit that is effective in a given jurisdiction. The effective DTI limit is calculated by taking the DSTI, stressed DSTI and maturity limits into account, and assuming a 2% interest rate. *For countries that do not have a maturity limit imposed, 30 years is assumed, as in Lithuania. ** For countries that do not have a DSTI limit imposed, a 40% DSTI limit is assumed, as in Lithuania. *** assuming that LTI = DTI, i.e. there is only a single loan per borrower.

2.4.1 Active changes in policy

While specific BBM limits of the ASN framework are usually seen as structural parameters, they may be used countercyclically to tackle misalignments – positive and negative. For example, Mendicino (2012) finds that time-varying LTV caps, which respond to the size of financial imbalances, are welfare-improving. Similar arguments have been made by multiple authors, including Lambertini et al. (2013), Mendicino and Punzi (2014), Rubio and Carrasco-Gallego (2014) or Bruneau et al. (2018).[13] More recently Gatt (2021) and Ferrero et al. (2022) look at LTV rules in a setting with occasionally binding constraints, and find that the LTV cap should be strongly countercyclical. Interestingly, Gatt (2021) shows that the time-varying LTV limit should react asymmetrically, i.e. tightening should occur more aggressively during credit booms, creating ample space for loosening during busts.[14]

While DSGE-based analyses overwhelmingly show that time-varying LTV rules can improve welfare, there are serious practical considerations of such policy set-up. First and foremost, the actual LTV ratio of loan contracts tends to be highly procyclical – it increases along with house prices during a boom, and significantly drops when crisis hits. This implies that the impact of tightening or easing the LTV cap or other BBM's is highly asymmetric across different stages of the credit cycle (e.g., see Richter et al., 2019). Most importantly, any expansionary BBM policy to support lending during a bust may not be effective, as lenders become risk-averse, and BBM-based requirements become less binding, if not obsolete.[15]

Second, conducting a policy of actively changing the BBM parameters is plainly hard from the policymaker's perspective. Implementation of such policy should be based on the identification of the phase of the financial cycle, which in itself is an enormous task, involving a plethora of different indicators that often contradict each other. Then, there are different time lags – acquisition of data for measurement of imbalances, process of policy implementation, and delayed impact. What is more, the effect of policy change

[13]Welfare gains from time-varying LTV rules are not uniform across different agents. Authors show that actively changing the LTV limit is optimal only from the borrower's perspective, whereby the saver would prefer keeping the LTV cap constant throughout the cycle. Although this implies a trade-off between saver's and borrower's welfare, in aggregate there are quite substantial macroecoconomic and financial stability gains from having a policy rule that entails a time-varying LTV ratio (Lambertini et al., 2013; Rubio and Carrasco-Gallego, 2014; Rubio and Comunale, 2016).

[14]Rubio and Comunale (2016) show that a high share of variable-rate mortgages, for a country like Lithuania, can slightly diminish the need to actively change the LTV limit, as monetary policy is better transmitted to the economy. Adding to that, Brzoza-Brzezina et al. (2014) find that interest payment type does not affect the magnitude of the effect of macroprudential policy, but can create strong asymmetries, with tightening having stronger effects than easing.

[15]Figure 2(c) shows that at the onset of the Covid-19 pandemic in Lithuania, the average and the 1st quartile LTV ratio decreased, as creditors became more cautious about the economic impact of the pandemic. In a similar, though significantly more pronounced fashion, the LTV ratio dropped during the 2009 financial crisis (see Figure 7 of Matkėnaitė et al., 2016). For a comparison of the two periods, please see Appendix D of Reichenbachas (2020).

is generally uncertain, particularly of an easing during a bust phase – it is unclear, who would take out mortgages at more lax conditions, and which credit institutions would be willing to take on more risk. In essence, active policymaking is prone to errors, which could do more harm than good, especially in the beginning learning stage of macroprudential framework.

Third, a single change in BBM's is highly distortionary for credit, housing and rental markets, let alone frequent changes that add an additional layer of uncertainty for market participants. While alterations in regulation definitely affect creditors – they have to comply with the new requirements and implement in their own risk-assessment frameworks; unexpected or frequent changes can be particularly hurtful for home-purchasing households, especially when they are financially constrained. From the customer's perspective, taking out a housing loan is a significant long-term decision, which requires financial planning and investment in down payment. Any unexpected tightening of BBM's, like the LTV requirement, will markedly alter any purchasing plans or arrangements, thus the household will likely have to choose a home of lesser quality, delay purchase or experience financial loss.[16] On the other hand, an early announcement of future increase in regulatory requirements would incentivise households to rush and take out a mortgage early, in aggregate causing a frontloading of the market and even accelerating the accumulation of imbalances. Generally, frequent changes in BBM parameters, in particular unexpected enforcements, would invoke uncertainty, generate public mistrust towards the regulator, leading to a likely reputational damage.

Last but not least, since BBM's affect housing affordability, the regulation is socially sensitive, thus there are substantial risks for the toolkit, or process of changing it, to become politicised. Frequent changes in BBM's may draw intrusive attention from politicians or special interest groups, lobbyists, who could try to influence the decision-making process, ultimately jeopardising the independence of the policymaking institution.

2.4.2 A one-off tightening

On the basis of the outlined arguments, one can see that the amount of operational issues, with regards to frequent changes in BBM limits, overwhelms the DSGE-based evidence. Perhaps that is why active changes in regulation, whether discretionary or rules-based, are rarely practised. As Matkėnaitė et al. (2016) argue, it may be good to have a long-standing BBM framework with fixed parameters, setting a standard for all market participants, promoting a sense of certainty. After all, LTV and DSTI limits

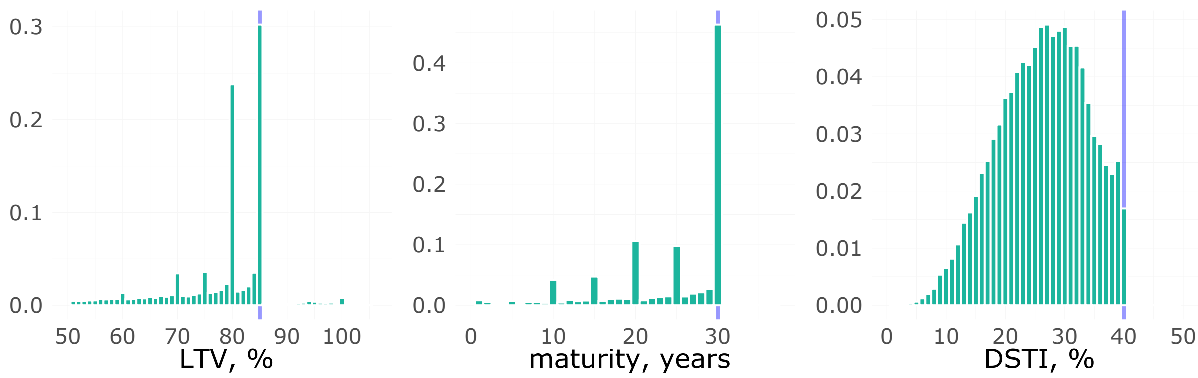
[16]Households often sign preliminary purchase agreements with sellers, e.g. real estate developers, and pay the down payment directly to them, expecting to secure a housing loan with prevailing ASN conditions. In this case, an unexpected decrease in the LTV requirement would imply a higher down payment, which for a financially constrained buyer could be unattainable. If there are no regulatory exemptions made by the regulator for preliminary agreements, this situation would force the buyer to forego the paid sum.

improve resilience and act countercyclically, even if they are unchanged throughout the cycle.

However, the latter logic does not rule out discrete changes in BBM's, when they are occasional recalibrations of the toolkit. On the contrary, if there is strong evidence, revealing that current macroprudential stance is inappropriate, e.g. loose, the regulator may act accordingly, e.g. tighten the regulation, as long as the alterations are not too frequent. This approach is supported by Brandao-Marques et al. (2020), who empirically find that the tightening of BBM's can be particularly beneficial, if financial vulnerabilities are on the rise. On the basis of this argument, current heat in the housing and credit markets could be contained by imposing stricter ASN limits. Otherwise, if no policy intervention was made, there could be a build-up of even greater vulnerabilities of systemic importance.

To understand what the options for tightening are, one could take a look at the bindingness of ASN parameters in Lithuania. Figure 4 shows that the LTV and maturity limits are significantly more binding than the prevailing DSTI cap. More precisely, around 37% of newly issued loans have a limiting LTV of 85%, and 48% have an LTV that is just below the cap, i.e. LTV $\in (80\%, 85\%]$. This implies that, if the regulator decided to tighten the LTV limit to 80%, roughly a half of the lending flow would be affected. Turning to the maturity limit, we observe that around 31% of the mortgage flow have maturity at the 30 year limit, and 64% of new loans would be affected by tightening of mortgage duration cap to 25 years. The corresponding figure for the DSTI cap of 40% would be only 1%, and tightening of DSTI cap to 35% would touch around 16% of new mortgage volume.

Figure 4: Distributions of LTV, maturity and DSTI for new housing loans



LTV = 85%	LTV > 80%	Maturity = 30y.	Maturity > 25y.	DSTI = 40%	DSTI > 35%
37%	48%	31%	64%	1%	16%

Notes: histograms for new mortgage contracts, which originated between October, 2019 and May, 2022. Vertical blue lines mark the regulatory ASN limits. The table below the histogram tabulates the share of mortgage volume at or around the corresponding regulatory limits.

As BBM parameters are usually set in 5 unit intervals (see Table 2), the tightening of LTV by 5 p.p. would be the most effective, compared to the impact of setting the DSTI limit to 35%. This is exactly the reason why we would argue that from a policymakers perspective, the tightening of the DSTI limit by 5 p.p. is a better option – it is less impactful, however, also less distortionary. A tightening of the LTV limit would significantly affect around half of mortgage issuance, mostly first-time-buyers, many of whom are financially constrained young families; independently of their risk profile. In a vast number of instances, credit institutions grant mortgages with a maximum LTV limit of 85%, or close to it, only if the housing collateral is of good quality and the debtor is of low risk. The tightening of LTV to 80% would disproportionately affect mortgage contracts that are of low risk, i.e. trustworthy borrowers with high-quality collateral.

On the other hand, if the DSTI option was chosen, it would affect around 15% of borrowers – roughly the size of mortgage overflow – whose DSTI is on the right-hand side of the distribution (see Figure 4b). Stricter regulation of $\text{DSTI}^{(*)}$ – headline DSTI or the stressed DSTI^{*} – would be more targeted to containment of risk, since the ratios are strongly related to customer's PD, as shown by multiple authors, including Mihai et al. (2018), Galán and Lamas (2019), Nier et al. (2019). Lastly, using a comprehensive framework, Gross and Población (2017) find that the "DSTI limit is more effective than LTV cap from the perspective of reducing household risk parameters while implying less pronounced macro feedback effects".

This section presented Lithuania's macroprudential BBM's – the ASN framework, and overviewed the recent mortgage market dynamics, which can lead to vulnerabilities, if no policy intervention was made. On the basis of this background discussion, the next section will develop a micro credit risk model, and later use it for an in-depth assessment of the $\text{DSTI}^{(*)}$ cap from the quantitative perspective, and lastly showcase the calibration exercise of the LTV limit for secondary mortgages.

3 Modelling mortgage risk

Any decision regarding the BBM's should be based on a model-driven analysis that, among all factors, takes into account credit risk. This section is devoted to contributing to the latter aspect of macroprudential policymaking by developing an econometric framework, which views how BBM's affect mortgage credit risk at the granular loan level.

Brief overview of methods

Taking a look at the macroprudential policy literature that focuses on the assessment or calibration of BBM's, there are at least four distinct approaches. The first is the most structural and least data-based method of DSGE modelling, which includes the previously mentioned examples of Lambertini et al. (2013), Rubio and Carrasco-Gallego (2014), Ferrero et al. (2022) and others, and also models that explicitly include mortgage default in Darracq Pariès et al. (2011), Forlati and Lambertini (2011), Clerc et al. (2015), Nookhwun and Tsomocos (2017), or Karmelavičius (2021) for Lithuania. While DSGE models can serve as a sandbox for experimenting with all sorts of policy rules and options in a general equilibrium setting, they lack accuracy that is necessary for calibration, and thus is the least practical approach.

The second approach deals with BBM analysis in an agent-based simulation setting, which takes into account the inherent heterogeneity across multiple borrowers and loan contracts, by typically exploiting survey data. Macroprudential policy literature that utilises agent-based models is relatively new and includes papers of Baptista et al. (2016), Cokayne (2019), Laliotis et al. (2020), Catapano et al. (2021), Tarne et al. (2022). This strand typically finds that BBM's reduce mortgage credit risk and slow down the credit and housing cycle, and that the impact of instruments is highly nonlinear, depending on the distribution of households and loan contracts. The latter finding confirms the importance of granular data for addressing household heterogeneity when calibrating BBM's.

The third strand dwells on the seminal paper of Gross and Población (2017), who develop an approach that integrates household-level survey data with a macroeconometric block, allowing to analyse how aggregate shocks are propagated to household default. The literature, which is based on the model and includes works of Jurča et al. (2020), Ampudia et al. (2021), Neugebauer et al. (2021), finds that BBM's noticeably improve household and bank resilience to macroeconomic shocks, and that different tools like LTV and DSTI caps reinforce each other when used in combination.

While the last two described methods rely on survey data and simulated default, the fourth approach is based on modelling the actual data of loan-level default. The approach involves regressing a default indicator on different borrower and loan characteristics, including BBM-based indicators like LTV, DSTI or DTI. This method is the most accurate and promising for calibration purposes, since it relies on exact default and loan data. However, due to the fact that micro level data availability and often quality are major obstacles for researchers, the use of such method is not as prevalent, as one could expect. Authors that exploit this approach include Kelly et al. (2015), Kelly and O'Toole (2018), Mihai et al. (2018), Galán and Lamas (2019), Nier et al. (2019), de Haan and Mastrogiacomo (2020), Andries et al. (2021), Kukk (2021). They typically find that BBM's, or indicators that are restricted by BBM parameters, significantly and often nonlinearly reduce the probability of default. On the other hand, authors mostly focus on the evaluation of the PD parameter, overlooking the LGD, and often ignore the time dimension of credit risk, solely focussing on one-year-ahead assessments.

Our modelling approach

This section and the rest of the paper are based on the above-mentioned fourth approach, which models actual loan-level events of default. This is enabled by the availability of high-quality granular data from Lithuania's credit register. Our PD model relates loan-level and borrower characteristics, including the BBM parameters at loan origination, to loan performance during its observed lifetime. Instead of merely relying on one-year-ahead PD models, we expand the usual BBM modelling setting and evaluate credit risk comprehensively by including both PD and LGD parameters into the analysis for computation of expected credit losses (ECL).

$$\text{Credit risk:} \quad \text{ECL} = \text{PD} \cdot \text{LGD}$$

As mortgages are long-term contracts, usually up to 30 years (see Figure 4), we generalise the one-year-ahead loss framework to compute the lifetime ECL. To this end, on the basis of the expected loan amortisation schedule, unconditional t-period PD and LGD parameters are computed. We proceed by first describing our dataset, then by outlining the estimation results of the PD model, and finally make a transition towards the lifetime ECL framework.

3.1 Data

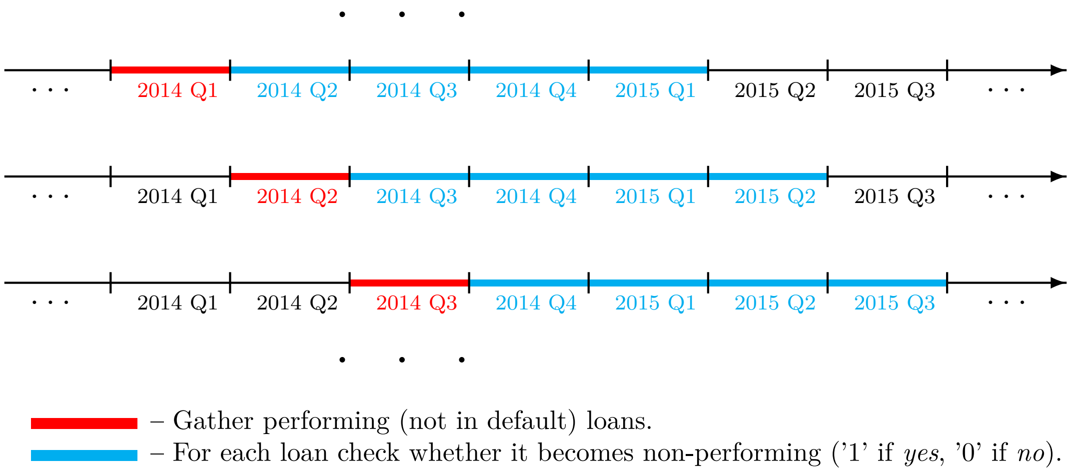
The main data source we use to model mortgage credit risk is Lithuania's household credit register which contains loan-level information about resident households' credit agreements.[17] The granularity of the dataset allows us to observe main household characteristics like family composition, income, economic activity type of each household member, as well as details about their credit obligations – amounts outstanding, interest rates, instalments, collateral values, residual maturities, and other variables. Importantly, the dataset includes a loan performance attribute, which indicates the current status of a loan – either it is active, delinquent for more than 60 or 90 days, or written-off. The data is observed at quarterly frequency and spans from 2004 to 2020, covering the boom-bust cycle surrounding the Global Financial Crisis, as well as the subsequent economic recovery. Additionally, we use macroeconomic time series like inflation, house price index, real GDP, unemployment rate and disposable income.

As we employ a binary regression model for actual loan-level defaults, a default indicator has to be defined. In line with the literature, we consider a loan to be in default, if it is either delinquent on payments for more than 90 days, or is written off. The dependent

[17] The dataset is NŪFSIS (*Lith.* Namų ūkių finansinės stebėsenos informacinė sistema; Household finance monitoring system) – a system that joins the credit register with household register and social insurance (SoDra) database. The same NŪFSIS database was used by Rutkauskas et al. (2015). A recent report on household finance, which utilises data from the database is available here (link).

variable for modelling the one-year-ahead PD is constructed using an iterative procedure, which is depicted in Figure 5. For every loan-quarter combination, we: a) assign '1', if the loan is performing at that quarter, but defaults within the next year; b) assign '0', if the loan is performing during the given quarter, and also performing within the next year; c) remove the observation altogether, if the loan is not performing at that particular quarter. Additionally, as credit history may be an important explanatory variable of future defaults, for each quarter we construct a binary indicator marking each household's historical performance aggregated across all loans over preceding three years.

Figure 5: Iterative construction of the dependent variable



Since BBM-related indicators are at the cornerstone of our analysis, we compute DSTI, DTI and LTV ratios that are not directly observed in the original dataset. To obtain a single loan's debt service amount, we assume that each loan follows an annuity payment schedule, i.e. the sum of monthly instalments and interest payments remains the same over the course of a loan. Given an average interest rate i, time to maturity in years M, and outstanding loan balance D, we have:

$$\text{Debt service amount} = D \cdot \frac{\frac{i}{12}}{\left(1 - (1 + \frac{i}{12})^{-12M}\right)}.$$

Each household's total debt service amount, or the numerator of the DSTI ratio, is obtained as a sum of debt service amounts across all individual loans, including leases, consumer loans and mortgages. As only gross income is provided in the credit register, we modify the variable by deducting applicable income taxes to compute the after-tax or net income. The numerator of DTI – household debt – is taken as a sum of outstanding balances of household's all credit agreements. Regarding the LTV ratio over the course of each loan, we take into account any possible appraisal in collateral value by indexing it to the national house price index.[18]

As we are interested in measuring mortgage-level credit risk, we take additional steps for cases when a single loan has multiple households-debtors: i) loan payback expenses, outstanding balance and monthly income are aggregated across all households; ii) categorical variables, like household economic activity type or credit history indicator, are taken from the highest income-earning household.

The resulting dataset spans both cross-sectional and time dimension, allowing to observe the evolution of each mortgage over time. Due to data quality issues, we are not able to observe mortgage defaults prior to 2012, effectively limiting our model fitting sample. Nonetheless, the training set still contains nearly 5 million records and periods of high incidence of default. As other indicators, besides default and credit history, are available preceding 2012, we are able to use our estimated model to predict historical PD parameters for each mortgage for the whole time period of 2004-2020.

3.2 One-year-ahead probability of default

The analytical framework of this paper is primarily based on credit risk and probability of default over the lifetime of a loan, however, we build it by first computing the one-year-ahead PD's, and later expand the time horizon. In particular, for every mortgage at a given quarter, we estimate the probability of becoming non-performing at least once within next year, using the following logistic regression model specification:

$$\operatorname{logit}(\mathrm{PD}_{k,t}) := \ln\left(\frac{\mathrm{PD}_{k,t}}{1-\mathrm{PD}_{k,t}}\right) = \beta_0 + \boldsymbol{\beta}_1^\top \mathbf{x}_{k,t} + \boldsymbol{\beta}_2^\top \mathbf{z}_{k,t} + \varphi\left(\mathrm{oBBM}_k\right), \tag{1}$$

where $\mathrm{PD}_{k,t}$ is the one-year-ahead PD for housing loan k at quarter t since origination measured in years[19], $\mathbf{x}_{k,t}$ is a vector containing household and loan characteristics, $\mathbf{z}_{k,t}$ are macroeconomic variables, and oBBM_k are BBM-related variables at the origination of loan contract k.

Since our analysis is focused on the evaluation of BBM's, we include $\mathrm{D(S)TI}^{(*)}$ and LTV ratios that were observed at the origination of each mortgage contract. The rationale for including these indicators "at-origination" (marked o·), rather than time-varying "current" values (marked c·), is that BBM's directly affect credit conditions only at the origination of a loan contract. Therefore, model specification in equation (1) allows us to assess how BBM limits may affect loan performance throughout its lifetime. Moreover, similarly to Kelly et al. (2015), Kelly and O'Toole (2018) and Mihai et al. (2018), we use the restricted

[18]To deal with outliers for the majority of continuous variables, we winsorise them by setting extreme values to some specific predefined quantile or threshold. For instance, we cap DSTI and LTV ratios at 300% and DTI at 67.

[19]One-year-ahead PD at l-th quarter since origination has index $t = l/4$.

cubic splines transformation $\varphi(\cdot)$ for income-based debt ratios $\left(\text{oD(S)TI}^{(*)} \text{ and oDTI}\right)$.[20] This non-parametric technique captures more intricate nonlinear effects of income-based variables on the default probability.

Estimation results

We estimate the logistic regression model using Maximum Likelihood and present the results in Table 5. Our baseline model, which is fitted on 4.8M observations, maintains a generous discriminatory power of around 90%, as measured by the AUROC statistic, calculated using the 5-fold cross-validation procedure (see Appendix B for details). In comparison, Kelly and O'Toole (2018) were able to fit a model with AUROC up to 73%, and Mihai et al. (2018) up to 80%. The main difference in discriminatory power compared to the two papers can be associated with the inclusion of credit history variables into our model, without whom the AUROC would be closer to that of Mihai et al. (2018).

Now, we briefly discuss the baseline model parameter estimates, which could be divided into three groups: i) borrower and loan features; ii) macroeconomic variables; iii) BBM-related variables (see column Model 1 in Table 5).

The first block includes various borrower and loan features, such as maturity, interest rate, income, credit history, etc. We can see that residual maturity of a loan is highly significant and positively related to one-year-ahead PD, meaning that customer default is more likely at the earlier stages of a housing loan's lifespan.[21] The results also suggest that higher interest rates may significantly increase the risk of default throughout the life cycle of a loan.[22] Very importantly, thus covered in much more depth in Section 5, the fact that a customer has more than one housing loan may statistically significantly increase the likelihood of mortgage default. Furthermore, model estimates suggest that borrowers that have more dependents and lower income are more likely to default. Both historical defaults in three-year credit history and short-term delinquency events (less than 90 days) positively affect future default probability, and also are highly significant for model's discriminatory power.[23]

Regarding macroeconomic variables, we can see that customer default frequency is

[20] The transformation can be described as a piecewise cubic polynomial, which is assumed to be continuous and have continuous first order derivatives at its knot points.

[21] This may be explained by the fact that at the beginning stages of a loan, the outstanding amount is still comparatively large and the customer is less keen in keeping that loan active. Also, at least for annuity schedules, instalments are more sensitive to changes in interest rates at early stages of a loan's lifetime.

[22] The impact of interest rates on loan default may be slightly overestimated, as there may be some degree of endogeneity – unobserved customer quality flaws may affect the PD and also result in higher interest rates as a compensation for higher credit risk.

[23] If a household had any issues repaying its credit agreements over the past three years, its mortgage default probability is on average 2.1 p.p. higher than that of historically solvent borrowers. If a housing loan is already delinquent for more than 60 days but not yet considered strictly in default, it is approximately 2.4 p.p. more likely that it will become non-performing over one year horizon.

counter-cyclical, i.e. PD is lower when the economy is growing, unemployment rate and inflation are low, albeit the magnitude of their impact is rather limited. Interestingly, unemployment rate is highly statistically significant at even the most conservative levels, suggesting that households' ability to service debt is dependent on labour market conditions. To control for possible unobserved factors related to looser lending conditions preceding the GFC, the regression includes dummy variables, which mark the year of loan origination. Model results suggest that loans that were granted before the GFC are statistically significantly riskier than the ones issued afterwards.

Turning to oLTV and oD(S)TI$^{(*)}$ variables, which are directly related to BBM limits, they are highly significant for mortgage default. Section 4 will cover these results extensively, but we can already see that loose BBM stance, i.e. allowance for high oBBM$_k$ values, may increase individual mortgage default risk. In line with papers of Gross and Población (2017), Jurča et al. (2020) or Ampudia et al. (2021), the magnitude of the impact of oDSTI measures on PD is higher compared to that of oLTV. Also, we can see that that the cubic spline terms of oD(S)TI$^{(*)}$ are statistically significant, suggesting of nonlinear effects.

3.3 Transition to lifetime expected credit losses

Any BBM like LTV or DSTI cap, or the limit on loan maturity, will affect the riskiness of a loan throughout its lifetime – not only the first year since origination. Therefore, a calibration of BBM instruments should take into account how BBM-related variables at origination affect successive loan evolution, i.e. period from initial recognition to final maturity. Also, one cannot solely focus on the evaluation of the PD parameter only, as credit risk is also related to LGD parameter. Having these arguments in mind, we transit our BBM-assessment framework from one-year-ahead PD's to lifetime ECL's.[24] The concept of credit risk assessment over the life cycle of a loan is crucial, since we seek to evaluate the potential interactions of loan maturity with other BBM's, like the DSTI cap.

3.3.1 Lifetime probability of default

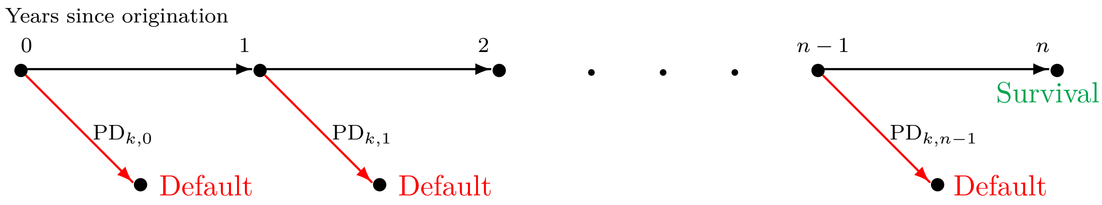
Now that we have the one-year-ahead PD model in place (see Section 3.2), we can expand the time horizon, and using the methods of survival analysis estimate lifetime PD's and loss rates.[25]

[24]Since the introduction of the new IFRS-9 accounting standards, survival analysis models became more prevalent in the context of credit risk assessment. According to the IFRS-9 regulations, loans whose credit risk increased significantly since their initial recognition, or which became impaired, are subject to measurement of lifetime ECL's.

[25]Our lifetime ECL formulae are similar to Buesa et al. (2019), although the latter paper purely focuses on IFRS-9 without estimating PD's at the loan level, and with no regard for macroprudential BBM's.

Assume, that loan k was issued with maturity of n years, as depicted in Figure 6. Let T_k be a random variable, which represents the time to first default in years of the

Figure 6: Loan lifetime evolution



k-th loan. As before, $\mathbf{x}_{k,t}$ and $\mathbf{z}_{k,t}$ denote time-varying household-loan characteristics and macroeconomic variables respectively for k-th housing loan at t-th year since origination. Then, one-year probabilities $\mathrm{PD}_{k,0}, \mathrm{PD}_{k,1}, \dots, \mathrm{PD}_{k,n-1}$ can be predicted using equation (1) estimates of Table 5. In fact, if we assume that loan default might occur only once during its lifetime and exclude the possibility of loan cures, each $\mathrm{PD}_{k,t}$, with $t = 0, \dots, n-1$, is a conditional probability:

$$\mathrm{PD}_{k,t} = \mathbb{P}\left(T_k \leq t+1 \mid T_k > t\right).$$

The unconditional probability of mortgage default during year $t+1$ since origination can be obtained as follows:

$$\mathbb{P}\left(T_k \leq t+1, T_k > t\right) = \mathbb{P}\left(T_k \leq t+1 \mid T_k > t\right)\mathbb{P}\left(T_k > t\right),$$

where

$$\begin{aligned}
\mathbb{P}\left(T_k > t\right) &= \mathbb{P}(T_k > t \mid T_k > l-1)\mathbb{P}(T_k > t-1) \\
&= \mathbb{P}(T_k > t \mid T_k > l-1)\mathbb{P}(T_k > t-1 \mid T_k > l-2)\dots\mathbb{P}(T_k > 0) \\
&= (1-\mathrm{PD}_{k,t-1})(1-\mathrm{PD}_{k,t-2})\dots(1-\mathrm{PD}_{k,0}) \\
&= \prod_{m=0}^{t-1}(1-\mathrm{PD}_{k,m}),
\end{aligned}$$

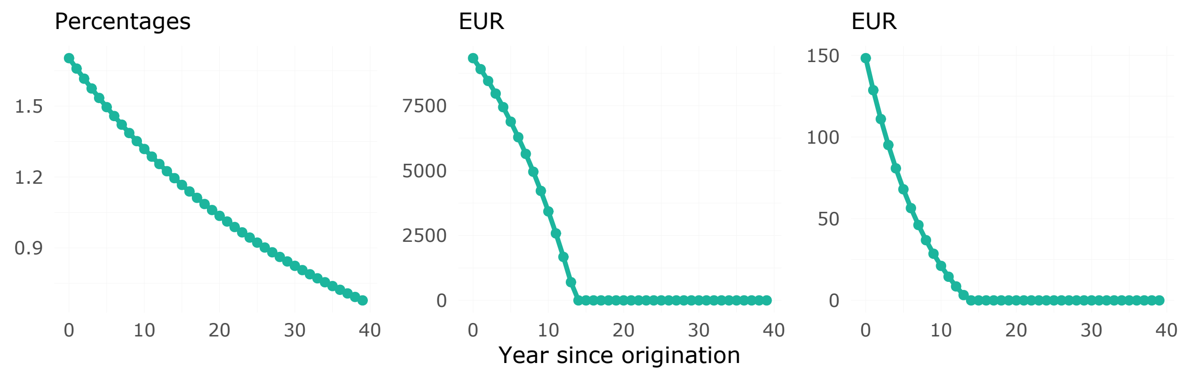
so that

$$\mathbb{P}\left(T_k \leq t+1, T_k > t\right) = \mathrm{PD}_{k,t}\prod_{m=0}^{t-1}(1-\mathrm{PD}_{k,m}). \tag{2}$$

As an example, we depict the evolution of unconditional PD throughout a loan's life cycle in Figure 7(a), computed using model estimates of Table 5. One can see that the probability of default at a particular year is declining towards the end of the loan's lifetime. This can be explained by two features: i) the coefficient on residual maturity is positively related to one-year-ahead PD (see Table 5); ii) naturally, the probability of survivorship is decreasing towards the end of the loan contract.

Figure 7: Point-in-time parameters over the life cycle of a loan

(a) Unconditional PD (b) LGD (c) ECL



Notes: (a) unconditional default probabilities obtained using expression (2); (b) LGD parameter is computed using equation (5) with $C = 5\%$ administrative costs, and assuming a 25% haircut to collateral value at the time of default (downturn LGD); (c) ECL's are calculated as pointwise products of corresponding unconditional PD's and LGD's.

The probability for loan k to default once during its lifetime of n years is equal to:

$$\mathrm{PD}_{k,n}^{LT} := \mathbb{P}(T_k \leq n) = 1 - \mathbb{P}(T_k > n) = 1 - \prod_{m=0}^{n-1} (1 - \mathrm{PD}_{k,m}). \tag{3}$$

Since the events $\{T_k \leq t+1, T_k > t\}$, with $t = 0, \ldots, n-1$, are disjoint, we can express lifetime PD alternatively, in terms of unconditional default probabilities:

$$\mathrm{PD}_{k,n}^{LT} = \sum_{m=0}^{n-1} \mathbb{P}\left(T_k \leq m+1, T_k > m\right) = \sum_{m=0}^{n-1} \mathrm{PD}_{k,m} \prod_{t=0}^{m-1} (1 - \mathrm{PD}_{k,t}). \tag{4}$$

3.3.2 Loss given default

In order to calculate the ECL for a mortgage, one needs to have estimates of losses that would be incurred in case of default. For each mortgage loan, the latter quantity is defined by the loss given default (LGD for short) parameter, which we compute using:

$$\mathrm{LGD}_{k,t} = \max\left\{\mathrm{EAD}_{k,t} \cdot (1 + C) - \mathrm{CLLT}_{k,t},\ 0\right\}, \tag{5}$$

where $\mathrm{EAD}_{k,t}$ is the exposure size at the time of default, and $\mathrm{CLLT}_{k,t}$ is collateral value. We assume that a fraction $C = 5\%$ of the $\mathrm{EAD}_{k,t}$ is attributable to administrative costs. Equation (5) implies that a creditor suffers losses, if collateral value does not cover the defaulted mortgage exposure and the administrative costs.

Figure 7(b) showcases the evolution of the LGD parameter since loan's inception, which is computed by assuming a loan's amortisation schedule. At the beginning phases of the loan contract, the LGD is positive and large, since the loan is not amortised yet.

Over time, the LGD vanishes to zero, as the loan is amortised and becomes relatively small to the value of the pledged collateral. By definition, the oLTV parameter is heavily linked to the collateral value and exposure at default, affecting the LGD throughout the loan's life cycle. The higher the LTV parameter of a loan, the more slowly the LGD parameter vanishes to zero, hence the creditor is more prone to experiencing losses in case of default.

3.3.3 Lifetime expected credit losses

Having expressions of unconditional PD and LGD at a given period t of a loan's life cycle, we can obtain the ECL for that period:

$$\mathrm{ECL}_{k,t} := \mathrm{LGD}_{k,t} \cdot \mathrm{PD}_{k,t} \prod_{m=0}^{t-1} (1 - \mathrm{PD}_{k,m}). \tag{6}$$

In essence, the above expression is a product of the unconditional PD and LGD at time t. It can be seen from Figure 7(c) that the ECL tends to diminish, as both the unconditional PD and LGD parameters are decreasing over time towards the end of the loan's life cycle.

Lifetime ECL's can be obtained by discounting and summing each period's ECL:

$$\mathrm{ECL}^{LT}_{k,n} := \sum_{t=1}^{n} \left[\underbrace{(1+i)^{-t}}_{\text{Discount factor}} \overbrace{\underbrace{\mathrm{LGD}_{k,t}}_{\substack{\text{LGD of}\\ \text{year } t}} \underbrace{\mathrm{PD}_{k,t} \prod_{l=0}^{t-1} (1 - \mathrm{PD}_{k,l})}_{\substack{\text{Unconditional PD}\\ \text{of year } t}}}^{\text{ECL of year } t} \right]. \tag{7}$$

The term $(1 + i_k)^{-t}$ denotes the k-th loan's discount factor, where i_k corresponds to the loan's interest rate.

3.3.4 Computation of lifetime credit risk at origination

Equations (2)-(7) lay theoretical foundations for assessment of lifetime credit risk. As our framework relies on prediction of one-year-ahead PD's using the estimated model in (1), we need to obtain values of explanatory variables $\mathbf{x}_{k,t}$ and $\mathbf{z}_{k,t}$ over the life cycle of a loan by making assumptions about mortgage amortisation and macroeconomic conditions.

For each mortgage that was issued between 2004 and 2020, we observe initial loan and household characteristics, and construct a hypothetical amortisation schedule. All mortgages and other household loans, including leases and consumer credits, are amortised to maturity in accordance to the annuity payment scheme, so that outstanding amounts and cLTV ratios are adjusted accordingly.[26] Household characteristics, like fam-

[26]Amortisation schedules need to be constructed for other household loans as well, since LTV-assessment exercise for secondary mortgages (Section 5) uses the DSTI metric, which includes all household loans.

ily composition, economic activity type and income group, as well as some loan-specific variables, such as interest rates and creditor dummies, are kept constant over the loan's lifetime. For simplicity, we also assume that household credit history will not worsen during a loan's lifespan, and that there will be no short-term delinquencies that are more than 60 days past due. As our PD model utilises BBM-related variables that are measured at-origination (oBBM_k), we keep them constant. Macroeconomic variables ($\mathbf{z}_t$), like real GDP growth, inflation and unemployment rates are fixed at their historic long-term averages, obtained using 1996-2022 data.

Having constructed the loan payment schedule for each loan in our data sample, we obtain vector-sequences of $\mathbf{x}_{k,t}$ and $\mathbf{z}_{k,t}$, and using equation (1) compute respective one-year-ahead probabilities $\mathrm{PD}_{k,t}$. Lastly, lifetime PD's and ECL's are estimated using equations (3) and (7).

This section described our mortgage risk modelling approach that builds a framework for the evaluation of lifetime credit risk by utilising the one-year-ahead PD model. The following two sections will use the described framework for the assessment of Lithuania's BBM's. Now that we have our modelling framework in place, we can use it to assess the efficacy of BBM's in Lithuania.

4 Assessment of borrower-based measures

Previously we discussed that ASN measures are in place in Lithuania since 2011, however, their efficacy is still under question as imbalances are emerging in the domestic housing credit market. In particular, there is an identified mortgage credit overflow of 15%, casting doubt on the policy toolkit's parametrisation – whether it is binding enough, especially in the period of low interest rates. If not, this could be tackled by a recalibration of the BBM's – a tightening of the DSTI limit or other measures, such as term maturity or LTV cap. The preliminary analysis of Section 2 suggests that a reduction in the DSTI limit is the most suitable policy alternative, since it is less distortionary and more targeted, compared to a further tightening of the already-stringent LTV cap. Nonetheless, it is far from clear what is the right DSTI cap from the perspective of credit risk. In this section we utilise the credit risk modelling framework of Section 3, and establish some empirical findings that address these concerns.

4.1 Efficacy of borrower-based measures

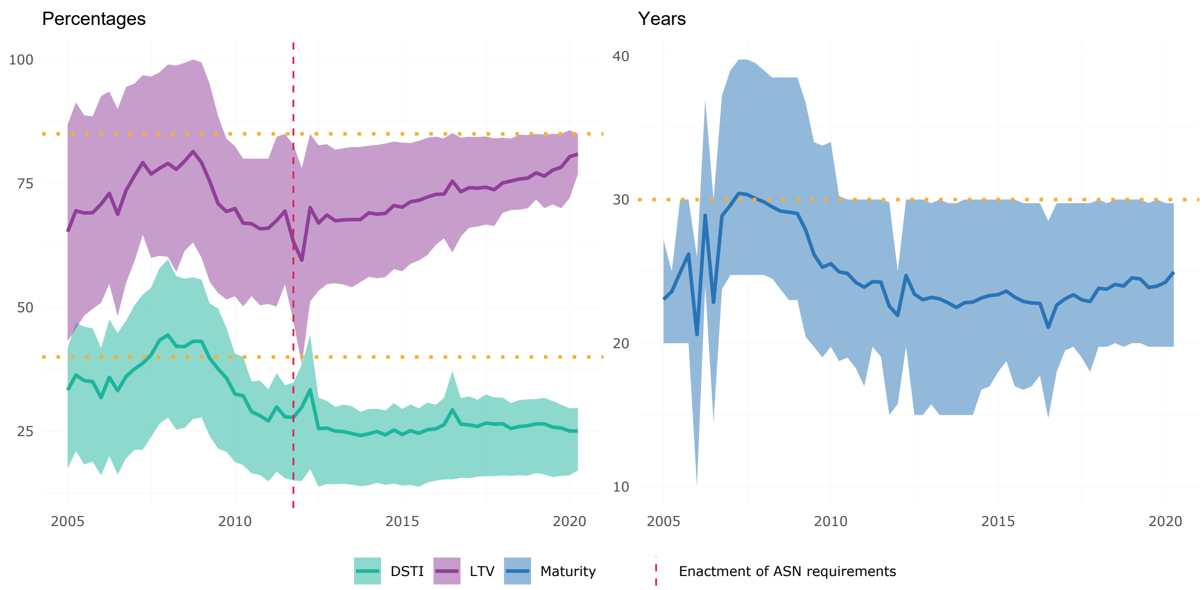
4.1.1 Mortgage quality preceding the GFC

In the 2000's preceding the GFC, Lithuanian household credit portfolio grew at a whopping 55% rate on an average annual basis. This process was partly enabled by then-low financial depth of the economy, and fuelled by abundant funding from abroad via Nordic bank subsidiaries, who were competing against each other and offering low credit margins (Karmelavičius et al., 2022a). As one can see from Figure 8(a) and (b), the competition was also asserted in a gradual deterioration in lending standards. Specifically, around 2008, a quarter of new mortgage issuance had LTV's that were as high as 100%. A similar dynamic took place for mortgage DSTI ratios and durations, as borrowers tried to compensate decaying housing affordability with higher indebtedness and ever longer maturities.

Figure 8: At-origination risk parameters for new mortgages

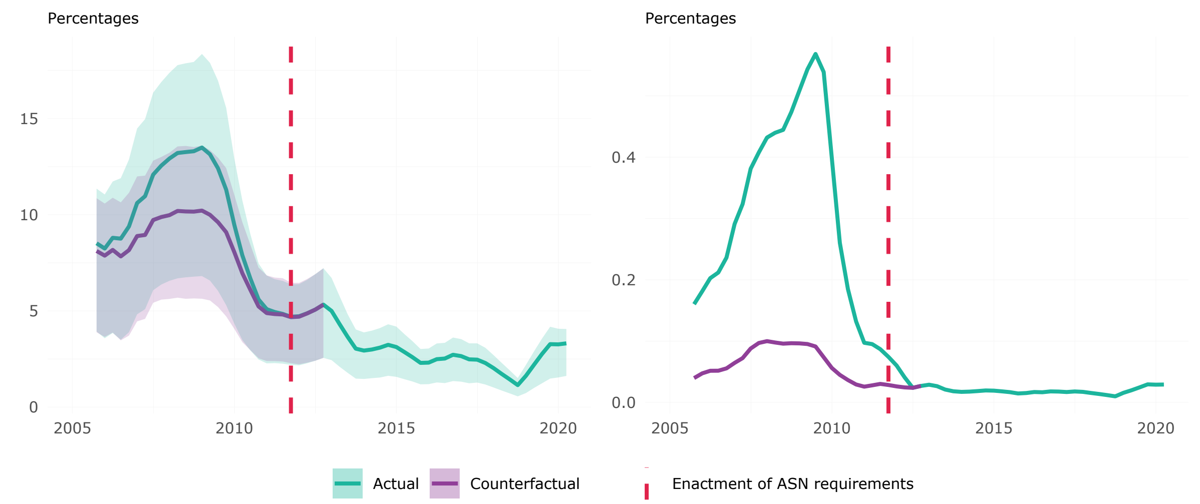
(a) LTV and DSTI

(b) Maturity



(c) Lifetime PD

(d) Lifetime ECL rate



Notes: (a) and (b) yellow dotted horizontal lines represent DSTI $\leq$ 40%, LTV $\leq$ 85% and Maturity $\leq 30y$. caps that are currently in place; (c) and (d) lifetime PD's and ECL rates are estimated at the moment of mortgage origination, utilising amortisation scheme as explained in Section 3.3.4, and assuming zero probability of recovery after default occurs. To reduce noise, data in panels (c) and (d) are smoothed over a rolling 1 year window; (d) ECL rate is calculated as a ratio of aggregate ECL's to sum of new mortgages.

We utilised our modelling framework of Section 3 and evaluated the underlying credit risk of individual mortgages that were issued preceding the GFC. As one can see from Figure 8(c) and (d), average at-origination lifetime PD gradually rose along with DSTI, LTV and maturity metrics, and reached 12% around year 2008. In essence, one-eighth of mortgages that were issued around 2008 should be defaulting at least once during their respective lifespans. Taking into account the LGD parameter of these loans, the at-origination lifetime ECL rate reached around 0.6%, implying that for every housing loan that was nominally worth 100 EUR, 0.6 EUR should have been set aside for future loss allowances.

Matkėnaitė et al. (2016) and Reichenbachas (2020) showed that had the LTV requirement of 85% been in place in Lithuania in the 2000's, credit and house price growth would have been much slower, and thus the banking sector would have experienced much smaller mortgage losses during the collapse of 2009. To complement their findings, which concern only the LTV limit, we conduct a similar exercise by looking at risk parameters that would have prevailed, if three of the current ASN measures had been present (see Table 1). In principle, for every mortgage that was issued before the implementation of the ASN framework in 2011, and would have breached any of the ASN requirements, we censor its maturity, DSTI and LTV metrics using the respective limits of 30 y., 40% and 85%. We do so by first limiting the maturity of a given mortgage and recalculating its DSTI ratio, and then proceed by reducing the loan amount, if DSTI and LTV caps were violated. Using this synthetic parametrisation for each loan issued prior to 2011, we predict its one-year-ahead PD, lifetime PD and ECL rate.[27]

The at-origination counterfactual estimates are presented by the purple line which lies significantly lower than the green one (Figure 8c and d). The results suggest that had current ASN limits been imposed in the 2000's, average credit risk of individual mortgages would have been significantly lower – lifetime PD by 2 p.p. and lifetime ECL rate by 0.3 p.p. This implies that the BBM package, if implemented, would have reduced mortgage ECL rate by 78% – in relative terms. Additionally, as people would had been taking smaller loans as a result of such hypothetical regulation, the mortgage portfolio would have been at least 24% smaller. By combining lower relative loss rate with lower mortgage volume, we compute that aggregate mortgage portfolio losses for the banking sector would

[27]This computation is a mere sensitivity analysis that does not take into account the probable outcome that some loans would have been issued later, or not issued at all, if ASN limits were present. Also, we do not account for possible macroeconomic feedback effects through reduced house price, credit and economic growth.

have been around 83% (= $[1 - (1 - 0.78)(1 - 0.24)] \times 100\%$) smaller.[28] This estimate of ASN package's impact on Lithuanian banking losses exactly coincides with Matkėnaitė et al. (2016) who take into account only the LTV limit. The following finding summarises our results:

Finding 1 *Had current ASN limits been imposed preceding the GFC, the credit risk of individual housing loans would have been significantly lower, and aggregate mortgage losses at least 83% smaller than those experienced by Lithuania's banking sector during the crisis.*

The latter finding does not take into account the potential general equilibrium effects of such regulation, which could have significantly reduced credit and house price growth (Reichenbachas, 2020), and possibly alleviated the impact of the recession, if not prevented it altogether.

4.1.2 Post-GFC period: ASN framework and borrower resilience

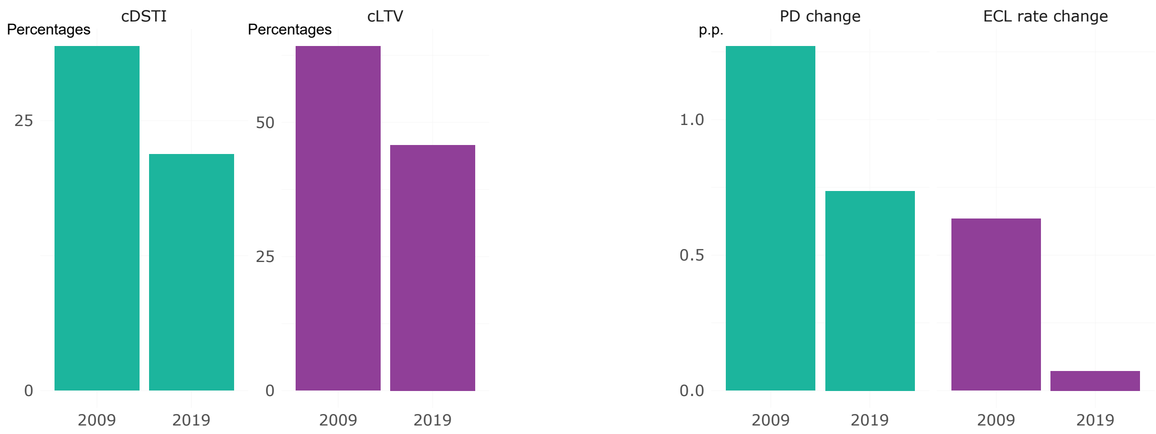
During the collapse of 2009, risk appetite plummeted and so did LTV and DSTI ratios, as well as mortgage maturities (Figure 8a and b). In fact, post-GFC period can be characterised by lenders' self-corrective behaviour, which may have stemmed from either a sudden change in sentiment or realisation of risk, or lessons learned from past errors. Therefore, ASN regulation that came into effect in 2011 was not immediately distortionary for the mortgage market (see also Matkėnaitė et al., 2016; Reichenbachas, 2020). Notwithstanding, the limits entailed by the rulebook set a standard for all market participants, including both creditors and debtors, suppressing the right-hand tail of the risk distribution, thus curtailing the procyclicality of risk appetite. This is vividly portrayed in Figure 8(a) and (b), wherein after 2011, the growth in the 75-th percentile of at-origination LTV's and maturities is limited by the respective BBM's.

Our credit risk model estimates suggest that in the 2010's lifetime PD's and ECL rates gradually declined and became significantly lower, compared to the pre-GFC period, thus the risk profile of new mortgage issuance improved (Figure 8c and d). Since changes in mortgage flow composition cumulate to changes in stock, mortgage portfolio current DSTI ratios and current LTV's substantially declined, as depicted in Figure 9(a). On the basis of portfolio data in 2009 and 2019, we conducted a stress test, which shows that mortgage portfolio credit risk parameters are now less sensitive to adverse changes in economic environment (Figure 9b). As ASN regulations curb risk-taking behaviour by disallowing

[28] In addition to that, we utilise an alternative PD model that uses the factual (current) cDSTI metric as a predictor, replacing the at-origination oDSTI (see Table 6). The cDSTI variable, unlike the oDSTI which is constant, evolves over the lifespan of each mortgage, thus the marginal impact on one-year-ahead PD (see Figure 10), lifetime PD and hence lifetime ECL rate is stronger. This alternative framework implies that ASN regulation's counterfactual lifetime PD would have been lower by 5 p.p., instead of 2 p.p., and the ECL rate by 0.4 p.p., instead of 0.3 p.p. This results in 87% (= $[1 - (1 - 0.83)(1 - 0.24)] \times 100\%$) smaller mortgage portfolio losses during the GFC – a bit larger estimate than 83%.

Figure 9: Mortgage portfolio quality and resilience to stress: 2009 and 2019

(a) Portfolio cLTV and cDSTI metrics (b) Stressed change in PD's and ECL rates



Notes: (b) bars represent changes in average mortgage one-year-ahead PD's and ECL rates under an adverse scenario. The scenario entails a GDP drop of -3%, a decrease in disposable income and house prices of -8% and -36%, respectively, inflation of 22% and a rise in unemployment rate by 8 p.p.

BBM-related parameters to be over the limit, they certainly play an important role in keeping lifetime credit risk anchored, and borrowers more resilient to negative shocks of both idiosyncratic and aggregate nature.

Finding 2 *In the 2010's, mortgage quality increased and borrowers are now more resilient to adverse shocks, compared to the pre-GFC period, at least partly due to the introduction of ASN regulations.*

The latter finding supplements those of Reichenbachas (2020), who shows that the cap on LTV ratio reduced credit growth, especially throughout 2016-2019 when the limit became more binding. In essence, BBM's can be effective in limiting credit risk and boosting resilience, and also curbing credit growth. On the other hand, recent emergence of house price overvaluation and credit overflow implies that the policy toolkit's current parametrisation does not eliminate misalignments altogether.

4.1.3 Comparison of instruments in predicting default

In the discussion above, we saw that the ASN package as a whole can be effective in containing credit risk (Findings 1 and 2), however, it is not yet clear what is the efficacy of individual instruments. Here we look at which of the BBM-related variables is best at predicting whether a housing loan will default, and thus is the most suitable policy target in order to contain risk. More concretely, we test how much each variable generates additional discriminatory power in terms of AUROC statistic for the one-year-ahead PD model.[29]

Specifically, we tested the predictive power of mortgage default of five BBM-related variables, namely the oDSTI, oDSTI*, oDTI and oLTV ratios, and maturity – all measured at origination. Although not directly regulated by the ASN document, the DTI ratio is additionally included into our analysis for two reasons. First, given a specific interest rate, current regulation of maturity and DSTI ratio implies an effective DTI bound. For example, a mortgage with a 2% interest rate has an effective DTI limit of 9.[30] Second, although DSTI limit is the most prevalent income-related indebtedness measure in Europe, some countries use DTI or LTI ratios to limit overall household indebtedness – Norway, Ireland and Denmark as a replacement for DSTI, Latvia and Slovakia as an additional tool (see Table 2). Therefore, alternatively or in addition to current ASN metrics, the DTI ratio limit could be imposed as well.

To assess the efficacy of different BBM's in determining mortgage default, we fitted five different model specifications for each of the BBM-related variables in Lithuania. The empty model, or specification (i), contains only the BBM variable of interest, in order to test its predictive power when other predictors are absent. Gradually through specifications (ii)-(iv), we introduce other variables, such as residual maturity, oLTV, interest rate, and finally estimate the full model. For each model, we implement the 5-fold cross validation procedure and compile AUROC statistics in Table 3.

Table 3: AUROC statistics for different one-year-ahead PD model specifications

$\mathbf{oBBM_k}$	(i)	(ii)	(iii)	(iv)	Full
oDSTI	0.7044	0.7047	0.7363	0.7476	0.9052
oDSTI*	0.6960	0.6963	0.7297	0.7424	0.9050
oDTI	0.6752	0.6787	0.7155	0.7324	0.9038
oLTV	0.6382	0.6385	0.6385	0.6521	0.9017
oMaturity	0.5271	0.5271	0.6416	0.6711	0.9017

Notes: AUROC estimates are compiled using a 5-fold cross validation procedure described in Appendix B Model validation. Each row-specification contains the corresponding oBBM_k variable and is augmented according to the following scheme:

(i) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \boldsymbol{\beta}_1^\top \varphi(\text{oBBM}_k)$;

(ii) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \boldsymbol{\beta}_1^\top \varphi(\text{oBBM}_k) + \beta_2 \text{Maturity}_{k,t}$;

(iii) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \boldsymbol{\beta}_1^\top \varphi(\text{oBBM}_k) + \beta_2 \text{Maturity}_{k,t} + \beta_3 \text{oLTV}_k$;

(iv) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \boldsymbol{\beta}_1^\top \varphi(\text{oBBM}_k) + \beta_2 \text{Maturity}_{k,t} + \beta_3 \text{oLTV}_k + \beta_4 \text{IR}_{k,t}$;

(v) Full model (equation 1).

[29] We focus only on the PD component of the credit risk, because we do not have actual loss data that we could use to empirically estimate the relationship between BBM-related variables and the factual LGD rate. Instead, our modelling framework computes the LGD based on loan's features (equation 5), primarily driven by the LTV ratio, what is consistent with the literature (e.g. Gross and Población, 2017; Ampudia et al., 2021).

[30] If one takes into account the stressed DSTI* cap of 50%, which implies an effective DSTI limit of 35%, under 2% interest rate, the effective DTI limit is 7.9.

Estimation results suggest that model specifications containing income-related indebtedness measures (oD(S)TI$^{(*)}$) have significantly higher discriminatory power compared to models that have the oLTV ratio or maturity term.[31] This is in line with the result of Gross and Población (2017) and related literature, who show that the DSTI ratio is more important for determining the PD, while LTV is the primary determinant of LGD parameter. Moreover, we can see from Table 3 that mortgage initial maturity does not add much predictive power for short-term or one-year-ahead default, however, it may be more important for the whole horizon in determining lifetime PD, what will be discussed in the next subsection. Interestingly, under the full model specification the predictive superiority of oD(S)TI$^{(*)}$ indicators diminishes. This can be explained by the fact that the full model incorporates other characteristics, such as household income and credit history, which are strong determinants of future default.

Looking more closely at the predictive accuracy within the oD(S)TI$^{(*)}$ group, we can see that the oDSTI metric has the highest discriminatory power in differentiating between loans that will perform and those that will not. While the stressed DSTI* measure of 50% was introduced in 2015 to alleviate the impact of potential increases in interest rates on mortgage PD, it does not hold any predictive advantage over the headline DSTI metric. On the contrary, the oDSTI variable is at least marginally better in terms of AUROC statistic for both the empty model (i) and the full specification. Firstly, the oDSTI and oDSTI* measures are essentially the same, differing only in the applied interest rate for computing loan payment size (see Section 2 for details). Secondly, our model's training dataset spans from 2012 to 2020, covering a period of low and decreasing interest rates. Therefore, the empirical advantage of the DSTI* cap remains to be seen in the near future, when households become constrained by increasing rates.

Unsurprisingly, the difference in predictive power between oDSTI and oDTI models is marginal, since the full model includes both maturity and interest rate, which together with a certain level of DTI, imply a specific DSTI ratio. However, if you move to the other side of the spectrum, i.e. the empty model which contains only the relevant oD(S)TI$^{(*)}$, we can see that the oDSTI's predictive advantage is stronger.
The discussed results can be applied to BBM's and generalised as the following finding:

Finding 3 *Effective containment of the one-year-ahead probability of mortgage default can be achieved using income-based measures, especially the headline DSTI cap, whereby the LTV measure is more suitable at controlling the loss given default parameter.*

[31] oLTV's effect on mortgage PD is significantly lower across model specifications, what may be explained by the lack of intention to default strategically in Lithuania – a full recourse system. What is more, the oLTV variable in the full model is less statistically significant than oDSTI variable and its coefficient is evidently smaller – one p.p. increase in oLTV has much more lower effect on PD than the same increase in oDSTI (Table 5). Nonetheless, oLTV ratio is a crucial factor as it directly affects the ECL through the LGD parameter (equations 5 and 6).

4.2 Recalibration towards tighter stance

In this subsection we explore various policy combinations of DSTI caps and maturity limits that would increase the tightness of ASN framework, in order to tackle the recent emergence of credit and house price gaps in the low-rate environment. We focus on DSTI$^{(*)}$ measures, which include both headline DSTI and the stressed DSTI*, since their tightening would be less distortionary and more risk-targeted via containment of mortgage PD, compared to a more stringent LTV policy (see Section 2.4 and Finding 3). As lower DSTI$^{(*)}$ cap would incentivise new borrowers to take out loans with extended maturities, we analyse the DSTI$^{(*)}$ cap in combination with the maturity limit and their joint impact on mortgage PD's and ECL rates.

4.2.1 Adequacy of DSTI$^{(*)}$ regulation

The observed credit overflow poses a question whether the regulatory stance is tight enough. Previously we discussed that for further tightening of the BBM's, DSTI$^{(*)}$ limit is the most sensible option. Nonetheless, it is unclear what is the right DSTI$^{(*)}$ limit from risk-based perspective. We address this issue by taking a look at the relationship between the DSTI$^{(*)}$ metric and default probability. The relationship is quantified using the one-year-ahead PD model (equation 1) where the oDSTI$^{(*)}$ predictor enters nonlinearly via a restricted cubic spline transformation $\varphi(\cdot)$, as in multiple other papers, including Kelly et al. (2015), Mihai et al. (2018), Kelly and O'Toole (2018), Nier et al. (2019), de Haan and Mastrogiacomo (2020), Andries et al. (2021).

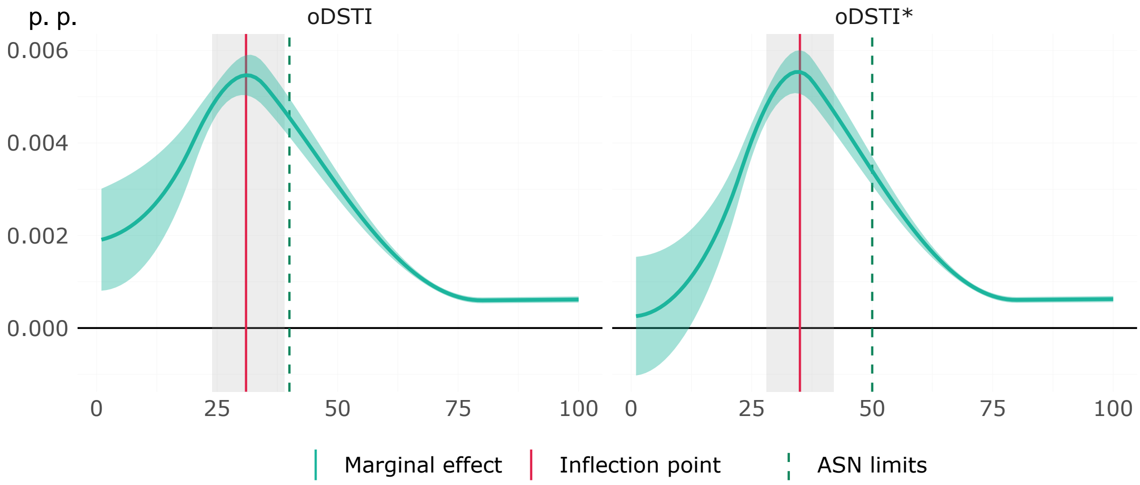
The fitted model presented in Appendix A Table 5 shows that income-based BBM variables measured at contract origination – oDSTI$^{(*)}$ – have highly statistically significant nonlinear effects on mortgage PD. In other words, at certain levels of oDSTI$^{(*)}$, PD responds more abruptly to changes in these variables, whereas at others, the reaction is much milder. Based on this finding we compute average pointwise marginal effects of oDSTI$^{(*)}$ on one-year PD and depict the relationship in Figure 10(a). Marginal effects are defined as partial derivatives of one-year-ahead PD with respect to oDSTI$^{(*)}$, evaluated at a particular level of oDSTI$^{(*)}$, assuming that other PD predictors are at their means and modes.

We can see from the chart that the point estimate – green solid line – lies above the zero axis globally, meaning that oDSTI$^{(*)}$ variables positively affect mortgage PD, albeit at differing magnitudes. At low levels of oDSTI$^{(*)}$, e.g. 0-10%, debt service is very small compared to income, thus changes in oDSTI$^{(*)}$ will not affect mortgage PD that much. On the other side of the curve where oDSTI$^{(*)}$ $> 60\%$, default risk is already large, therefore, any increment in oDSTI$^{(*)}$ will do little to the PD rate. Between these two low-risk and high-risk regions, lies a level of oDSTI$^{(*)}$ where the marginal impact on mortgage PD is the highest. Quantitatively, the inflection point for the oDSTI metric is equal to 31%

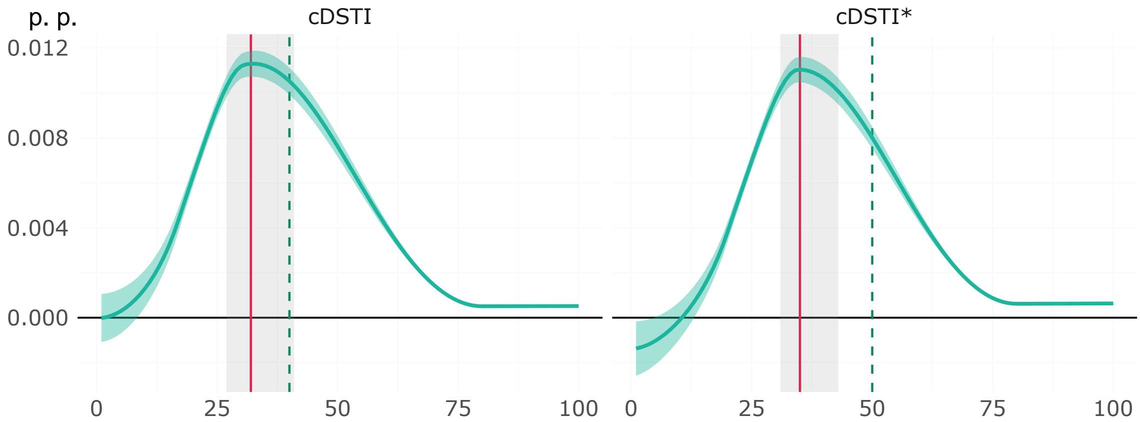
with confidence interval of [24, 39], and 35% [28, 42] for the stressed oDSTI*.

Figure 10: Average marginal effects of DSTI$^{(*)}$ on one-year PD

(a) model with oDSTI$^{(*)}$



(b) model with cDSTI$^{(*)}$



	DSTI	DSTI*
Existing limit	40	50
oDSTI$^{(*)}$	31 [24, 39]	35 [28, 42]
cDSTI$^{(*)}$	32 [27, 41]	35 [31, 43]

Notes: green area around the green curve corresponds to the 95% confidence interval for marginal effect estimate. Grey area around the red vertical line corresponds to a 95% confidence interval estimate of the inflection point. The mapping is based on estimated equation (1) in Table 5 columns 1 and 2.

If at these levels of oDSTI$^{(*)}$ mortgage PD grows very quickly, a creditor or the regulator may want to limit the oDSTI$^{(*)}$ values even before, so that PD growth does not reach this highpoint.[32] Nonetheless, it happens so that ASN framework's current parametrisation (oDSTI $\leq$ 40% and oDSTI* $\leq$ 50%) is already beyond those inflection points which

[32]Some authors find the oDSTI to be "optimal" where the marginal effect curve takes off the zero axis, i.e. impact of oDSTI becomes significantly positive (e.g. see Nier et al., 2019). In our case it already happens at very low values of oDSTI$^{(*)}$, thus we look at the point of where the speed of PD increment is the highest. We deem that the BBM-relevant oDSTI$^{(*)}$ cap should be calibrated to be lower than that inflection point.

are obtained using the PD model (oDSTI $\sim$ 31% $[24, 39]$ and oDSTI* $\sim$ 35% $[28, 42]$), suggesting that there is room for tightening of income-based requirements, at least the stressed DSTI*.

To check the robustness of these results, we additionally estimated marginal effects for the PD model where current cDSTI$^{(*)}$ ratio is used in place of at-origination oDSTI$^{(*)}$ (see Table 6 of Appendix A).[33] Figure 10(b) shows that while the resulting marginal effects are now stronger compared to the baseline oDSTI$^{(*)}$ model, the nonlinear shape is more or less preserved. With regards to inflection point estimates (red vertical lines), transition from oDSTI to cDSTI does not change them. However, we can see from Figure 10(b) that cDSTI inflection interval (grey area) overlaps current ASN 40% regulatory limit, whereas stressed DSTI* limit is still way beyond the corresponding DSTI* inflection interval. The latter result holds even if we remove other predictors from the model, arriving at the *empty* model specification where only the cDSTI* variable is present. In essence, different model specification estimates based on 2012-2020 data which coincided with low-rate period suggest that DSTI$^{(*)}$ caps were on the loose side, especially the stressed DSTI* limit.

Our results can be summarised in the following finding:

Finding 4 *The nonlinear relationship between DSTI$^{(*)}$ variables and the estimated probability of mortgage default suggest that under the low-rate environment the existing DSTI$^{(*)}$ limits were loose, especially the interest rate-stressed DSTI* cap which could have been lowered from 50% to around 40%.*

The above analysis favours the tightening of DSTI$^{(*)}$ limits as current ASN parametrisation is suboptimal from the PD-impact perspective, and additionally does not prevent the emergence of credit misalignments.

4.2.2 Combination of DSTI$^{(*)}$ and maturity limits

While the previous subsection inquires into the nonlinear relationship between DSTI$^{(*)}$ measures and mortgage default, it does not account for the time dimension of mortgages. We argue that a sound analysis of income-based measures should also involve the maturity limit, because a more stringent regulation of, say, the DSTI cap will likely cause borrowers to shift to longer durations, limiting the policy's effectiveness. For our analysis, we take the PD model and see how DSTI$^{(*)}$ metrics in conjunction with maturity affect mortgage default.[34] We start by looking at the one-year-ahead PD and later expand into lifetime PD framework.

[33] See footnote 28.

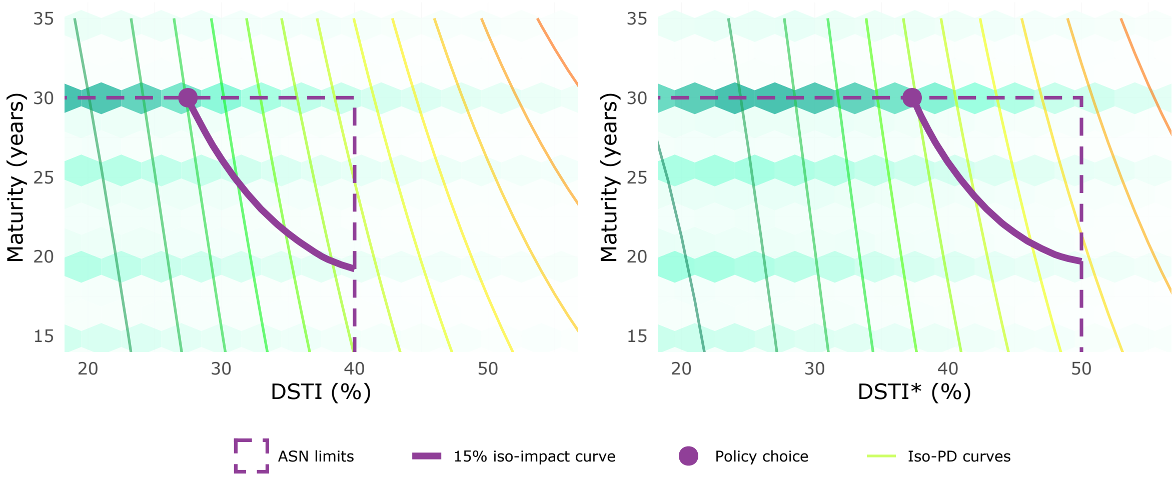
[34] The model that we use for this analysis contains current cDSTI$^{(*)}$ and residual maturity variable, instead of at-origination oDSTI$^{(*)}$ and initial maturity. However, as we compute PD's at the origination of a loan agreement, current metrics exactly coincide with their at-origination values. The reason we choose cDSTI$^{(*)}$ variable is that it better resembles the riskiness of a loan throughout its lifespan, rather than the non-changing oDSTI$^{(*)}$ variable.

(a) One-year horizon

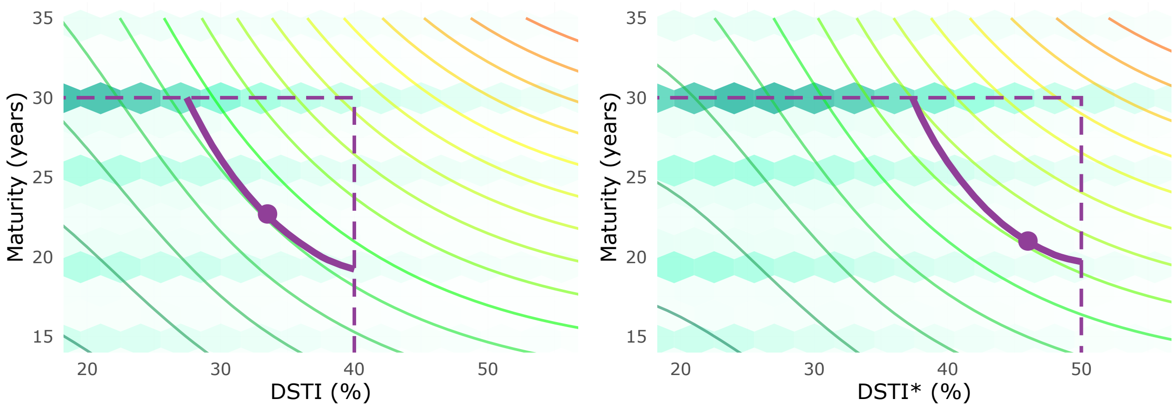
Suppose a regulator chooses a certain level of mortgage PD that is within her risk tolerance bounds. A natural question arises: what is the combination of DSTI$^{(*)}$ and maturity limits within the realm of ASN regulation that would ensure such PD level? To answer this question, there are many. In fact, a continuum of policy combinations that achieve a certain level of default probability can be visualised as an iso-PD curve. Figure 11(a) plots a map of such one-year-ahead iso-PD curves by a green-yellow-red contour. The farther an iso-PD curve lies from the origin $\{0\%, 0y.\}$, the higher PD level it represents.

Figure 11: Iso-PD and iso-impact curves for combinations of DSTI$^{(*)}$ and maturity limits

(a) one-year horizon



(b) lifetime horizon



Notes: dashed purple rectangle represents existing caps on maturity and DSTI$^{(*)}$. Solid purple curve corresponds to possible combinations of maturity and DSTI$^{(*)}$ limits that would reduce new mortgage flow by 15% (see Appendix C for details). Green-yellow-red contour represents iso-PD curves which map policy combinations to a specific level of either one-year (a), or lifetime PD (b). Hexagon-shaped points mark the actual distribution of new mortgage loan characteristics.

While policy calibration that is founded on some "appropriate" level of PD and a corresponding iso-PD curve seems appealing, a difficulty lies in the fact that it is entirely unclear what is that appropriate level, rendering such process highly subjective. Our previous analysis of misalignments in Section 2 showed that there is a 15% credit overflow, whose closure may be a policy objective. Assuming that, Figure 11(a) also contains solid purple curves, which represent different DSTI$^{(*)}$ and maturity policy duplets that would reduce the nominal credit flow by 15%. From policy effectiveness perspective, each policy combination on that iso-impact curve is equally good in closing the credit gap. For instance, DSTI and maturity limits of $\{28\%, 30y.\}$ or $\{35\%, 22y.\}$ would reach the same outcome in terms of reduced credit flow, compared to the current policy limit of $\{40\%, 30y.\}$. Note that the construction of this iso-impact purple curve is subject to household behaviour assumptions, and is described in Appendix C.

By the very definition, policy combinations on a single iso-impact curve can achieve the same impact on credit flow volume. Nonetheless, these different policy mixes will not necessarily be equivalent from risk perspective. This is exactly where iso-impact and iso-PD curves come together, as visualised in Figure 11(a). One can see that the left-most corner of the iso-impact curve corresponds to a one-year iso-PD curve that is closer to the origin $\{0\%, 0y.\}$, thus representing lower risk. The other side of the purple curve crosses an iso-PD curve that is farther away from the origin, corresponding to a higher risk policy combination. Therefore, the most sensible policy solution would be to choose a point on the purple curve where it crosses, or touches, an iso-PD that is closest to the origin. More simply, the purple points in the chart guide on which policy combination to choose in order to achieve the desirable impact with minimal individual mortgage credit risk.

Based on that, the most suitable policy option that is aimed at closing the housing credit gap of 15%, while minimising micro-credit risk, would be to reduce either the DSTI limit to around 30%, or the stressed DSTI* to 40%, leaving the maturity limit of 30 y. unchanged.[35] Since the current regulatory cap of DSTI $\leq$ 40% is within the confidence bounds of "optimal" policy, as suggested by the marginal effect curves in Figure 10, reduction in the stressed DSTI* limit to 40% may be a better choice. Effectively, such policy move would make the DSTI limit of 40% obsolete, as it would be shadowed by the new DSTI* $\leq$ 40% cap.[36]

(b) Lifetime horizon

It is sensible to assume that loans with longer maturities are more likely to default over their lifespans even at reasonable levels of DSTI$^{(*)}$ – as much as a car is more likely to crash on longer journeys even when driving at reasonable speed. Therefore, it is necessary to take into account the duration of a housing loan by utilising the lifetime PD framework,

[35] Purple points of Figure 11(a) actually stand on DSTI $\leq$ 28% and DSTI* $\leq$ 38% limits. Nevertheless, we round these numbers up to integers that are spaced by 5 units (p.p. and y.).

[36] The limit of DSTI $\leq$ 40% would become non-binding since DSTI* $\leq$ 40% would be a tighter measure. This can be seen from this inequality: $\text{DSTI}^*(\text{DTI}, \max\{i, 5\%\}) \geq \text{DSTI}(\text{DTI}, i)$.

rather than solely using the one-year-ahead model.

One can see from definitional equations (3) and (4) that lifetime PD increases monotonically along with increasing loan maturity n, assuming that DSTI$^{(*)}$ and other variables are constant. This is the reason why lifetime iso-PD curves depicted in Figure 11(b) become flatter, or less steep, than their one-year counterparts. Under the one-year setting, the length of horizon needs to change quickly in order to keep the PD rate constant when DSTI$^{(*)}$ limit is moving, as the DSTI$^{(*)}$ is the primary determinant of default. Now, under the lifetime setting, since loan duration becomes an important determinant of PD, the marginal rate of substitution between changing loan's duration and DSTI$^{(*)}$ metric becomes moderate and the iso-PD curve map in panel (b) is more convex.

The minimisation of lifetime PD while targeting the desired policy impact of 15% credit reduction, is now in favour of reducing both the DSTI$^{(*)}$ cap and the maturity limit. This can be seen from Figure 11(b) where an iso-PD curve for DSTI and maturity is tangent to the purple iso-impact curve at point $\{34\%, 23y.\}$. A similar conclusion can be made for DSTI* cap, where the minimal credit risk policy choice would be $\{46\%, 22y.\}$.

A map of iso-PD and iso-impact curves can serve as a powerful tool in studying policy alternatives that are aimed at achieving some desired outcome of credit volume reduction, while minimising individual mortgage credit risk. If our analysis focusses on the one-year horizon, we get a corner solution of reducing only the DSTI$^{(*)}$ limit. This policy recommendation would be compatible with Finding 4 of currently suboptimal ASN limits for income-based variables. If we expand our analytical horizon and look how mortgage loans perform over their whole lifespans, the minimal-risk policy solution would be to reduce both the DSTI$^{(*)}$ cap and the maturity limit. This subsection's results can be summarised by the following statement:

Finding 5 *Since longer maturity loans may, ceteris paribus, have a higher chance of defaulting at least once during their lifespans, minimisation of lifetime credit risk while achieving a desired policy impact can be accomplished through a joint reduction in both DSTI$^{(*)}$ and maturity limits.*

This section's analytical framework suggests that the "optimality" of the stressed DSTI* limit of 50% may be questionable, therefore the regulator may either reduce the DSTI* cap to around 40%, or limit both DSTI* and maturity to around 45% and 20y., respectively. While both options would reduce mortgage credit flow by approximately 15% and effectively close the credit gap, the latter joint tightening of DSTI* and maturity limits would minimise lifetime credit risk for individual housing loans.

However, it is of utmost importance to realise that mortgage interest rates are on a rise due to a sharp change in monetary policy stance, what is not taken into account in the above analysis. Based on Karmelavičius et al. (2022b), a 3 p.p. increase in mortgage rates could translate into a 12% decrease of mortgage flow, essentially eliminating $\frac{4}{5}$ of the credit overflow. Besides the price impact on reduced mortgage demand, increasing rates are already elevating average mortgage DSTI's from 27% to 30%, effectively making the 40% cap binding for some fraction of borrowers. This suggests that as interest rates continue to rise, current parametrisation of ASN regulation will become more binding and effective in stabilising credit flows, rendering any policy tightening action unnecessary.

5 Loan-to-value limit for secondary mortgages

To address the increasing prevalence of secondary and subsequent housing loans, Bank of Lithuania strengthened secondary mortgage regulation by imposing a tighter down payment requirement that came into force on February 1, 2022. If a household's first, and still active, mortgage current LTV ratio is higher than 50%, the household may finance an additional home purchase with a secondary mortgage of only up to a 70% LTV limit. For borrowers whose first active mortgage loan has a cLTV that is lower than 50%, secondary mortgage LTV ratio must be lower than 85%. While this new regulation has not been intended to be highly impactful for the housing market as a whole, it targets a segment that poses unnecessary risks, which the market had failed to address on its own.

This section sheds light on the credit risk aspect of the discussion that took place in 2021 when evaluating the need for and formulating the stringency of the amended regulation. First, we show how secondary mortgages are different in their risk profile compared to single mortgage loans.[37] Second, we outline a secondary mortgage LTV limit micro-calibration exercise that intends to equalise the credit risk of secondary loans to single mortgages.

5.1 Probability of default differential

Previously in Section 2 we discussed that secondary mortgages are riskier as they tend to default around 50% more often. This phenomenon at least to some extent may be explained by the fact that the DSTI ratio for secondary mortgages is usually significantly higher than that of first mortgage loans (see Figure 3b and c). Since DSTI ratio is a major determinant of loan default probability, this naturally translates into higher factual default rates on secondary mortgages. Having this in mind, one may conclude that additional regulation of secondary mortgages is unnecessary, as the primary component of mortgage PD, the DSTI ratio, is already limited by ASN requirements to 40%, hence risks are contained.

[37] We call a housing loan *single*, if it is solitary within a household's debt pool at a given point of time, i.e. there are no other mortgages. A first mortgage is not necessarily single, since at a given point of time there may exist a secondary mortgage that originated later than the first loan.

However, the question is whether the sole fact that a loan is secondary *per se* could be linked to a higher incidence of default, even when DSTI is constant. To answer this, we take a look at our one-year PD modelling results that are tabulated in Table 5 of Appendix A. Across all specifications, a mortgage loan is statistically significantly more likely to default, if the borrowing household has other active mortgage loans. We can see that the latter effect's magnitude positively depends on other housing loan's cLTV ratio. Moreover, the fact that a mortgage is secondary, in terms of chronological order, additionally increases the one-year PD. These findings suggest that secondary mortgages, which are by definition non-single and secondary in time of origination, are indeed more likely to default, even when the DSTI ratio, income group and other borrower-loan features are controlled for. This can be explained by at least two arguments. Secondary mortgages are often used to finance: i) buy-to-let investment that is subject to risk of loss of rental income, which may be more unstable than labour income; ii) acquisition of non-primary residence to which households may be less attached and less inclined to service their debt payments.[38]

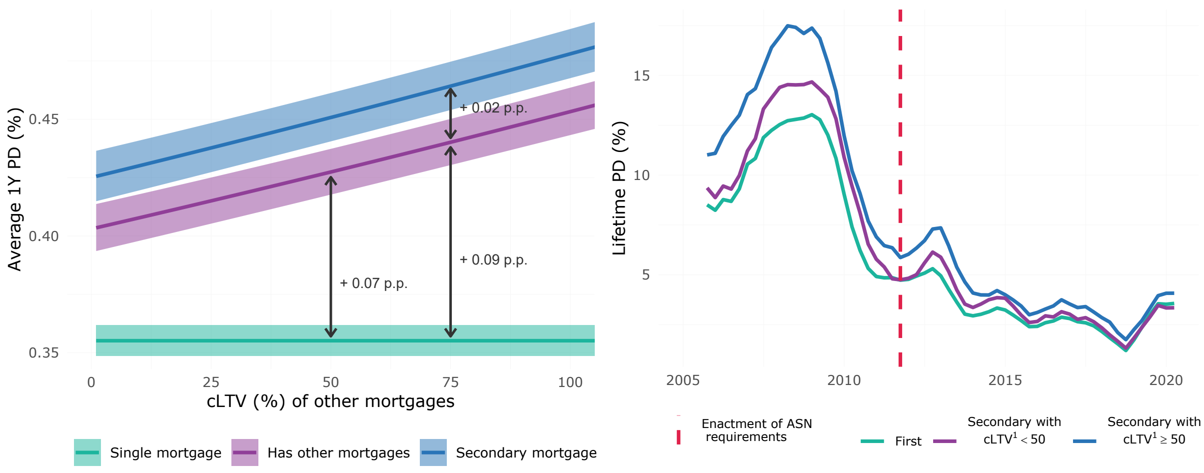
To understand more about economic rather than statistical significance of these results, we depicted their probability-impact in Figure 12. The green horizontal line of panel (a) marks the average one-year-ahead PD for a mortgage, whose debtor-household does not have any other mortgage loans, and other predictors of the model are kept constant at their means and modes. The upward sloping purple line shows the corresponding predicted PD rate, if the mortgage was non-single, i.e. the household has other active mortgage loans. We can see from the chart that the sole fact that the household has other active housing loans adds up to 0.12 p.p. in terms PD, depending on the cLTV level of other mortgages. For instance, if other mortgages' cLTV ratio is around 50%, the PD-differential is only 0.07 p.p. However, when the cLTV ratio of other mortgages reaches 75%, the PD-differential becomes equal to 0.09 p.p. Moreover, the blue line, which represents a case when the analysed mortgage is not only non-single, but also second in timing of origination, adds an additional 0.02 p.p. to the PD rate.

In summary, a secondary loan, whose predecessor-mortgage cLTV is 75%, may be 0.11 ($= 0.09 + 0.02$) p.p. more likely to default, compared to an otherwise equivalent but a single housing loan. The catch is that not only the secondary mortgage is riskier, but its mere origination increases the likelihood of default of the previous, or first, mortgage loan. As both housing loans have higher individual PD rates, the household-level PD increases even more – it becomes quite likely that at least one of the household's mortgages will become non-performing. This is in line with a conclusion of Kelly and O'Toole (2018), who find multi-loan borrowers to be more inclined to default. From the financial stability perspective, secondary mortgages are not only more likely to default individually, but

[38] Although at a smaller magnitude, our findings still hold when the cDSTI ratio is used as PD predictor, instead of oDSTI measure (see Table 6 of Appendix A).

Figure 12: PD differential of secondary mortgages

(a) Impact on one-year PD (b) At-origination lifetime PD averages



Notes: (a) solid curves represent average predicted portfolio one-year PD level conditioned on other mortgages cLTV ratio. Other explanatory variables are either fixed at their averages (continuous variables) or modes (factor variables). Bands around the conditional effects curves correspond to 90% confidence intervals.

they also impose a negative externality in terms of heightened credit risk for the existing portfolio of housing loans.

While the above discussed one-year PD differential of 0.11 p.p. may seem small, it becomes amplified when moving to a lifetime horizon. Using our modelling framework, we compute at-origination lifetime PD rates for first and secondary mortgages, and depict the average estimates in panel (b) of Figure 12. One can see that the purple and blue curves, representing at-origination lifetime PD's for secondary mortgages, lie globally above the green curve, which represents first and single mortgages. Throughout history, lifetime PD rate has been on average 3 p.p. higher for secondary mortgages compared to that of first mortgage loans. As suggested by the one-year PD model, secondary mortgages whose predecessor-housing loans have cLTV $\geq 50\%$, have an even higher chance to default at least once throughout their lifespans with PD difference equal to 3.5 p.p. Although lifetime PD's declined quite significantly in the post-GFC period, and continued to decrease after the inception of ASN framework in 2011, lifetime PD differences between first and secondary mortgages are still non-negligible, equalling around 0.4 p.p. over the last decade. To summarise our results, we state the following finding:

Finding 6 *Secondary mortgages: a) are more likely to default over their lifetime compared to an otherwise equivalent but single mortgage loan; b) impose a negative externality in terms of heightened default rate on the existing housing loan portfolio.*

5.2 Micro-calibration exercise

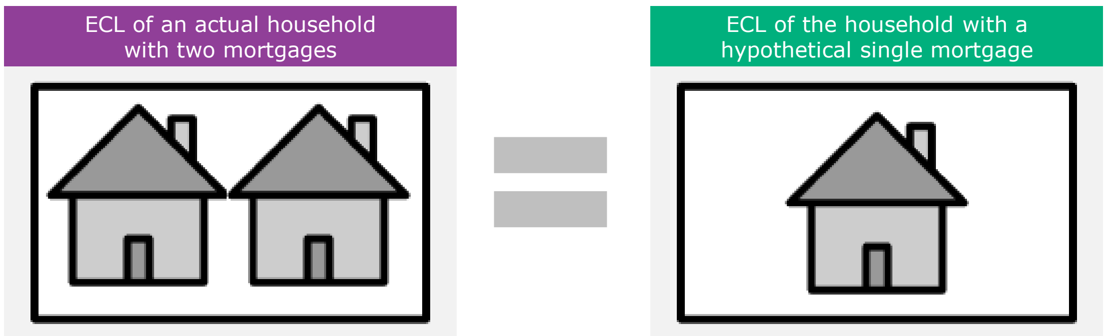
As discussed, secondary mortgages exhibit higher PD rates, and they also raise the PD of corresponding first housing loans. To compensate for that, credit institutions or regulators may want to decrease the LGD parameter to keep each multiple-mortgage household's credit risk anchored. While it is possible to directly affect secondary mortgage LGD^2 parameter by restricting LTV^2 at origination, first mortgage's LTV^1 ratio and hence LGD^1 parameter are predetermined.

Here we calibrate the LTV^2 policy limit, so that a debtor with multiple mortgages would exhibit a level of credit risk that is equal to that of a single-mortgage borrower.[39] We call this exercise micro-calibration as it takes into account only the micro-credit risk component, and abstracts from second round effects and larger externalities that are of macroprudential nature. This exercise could be used as a starting point in choosing an appropriate macroprudential LTV^2 limit, as experienced by the Bank of Lithuania. First, we will briefly outline our method, and then explain the results for the one-year and lifetime horizons, utilising the model framework of Section 3.

5.2.1 Calibration method

The calibration exercise entails finding a secondary LTV^2 limit which would equalise the credit risk to that of a single mortgage. Specifically, for each household that took out an actual secondary housing loan, we seek to find a personal LTV^2 limit, such that the aggregate ECL of both loans would be equal to the ECL of a single hypothetical loan, as depicted in Figure 13.

Figure 13: Calibration of LTV^2 limit: equalisation of ECL's



$$\mathrm{ECL}^1_h\left(\mathrm{LTV}^1_h, \overline{\mathrm{LTV}}^2_h\right) + \mathrm{ECL}^2_h\left(\overline{\mathrm{LTV}}^2_h, \mathrm{LTV}^1_h\right) = \mathrm{ECL}^H_h$$

[39] Preliminary results of this calibration exercise under the one-year setting were published as a popular commentary (link to article in Lithuanian). The article additionally contains calibration results that are founded on the micro-macro framework of Gross and Población (2017), that is based on simulated household-level mortgage PD framework, rather than loan-level model. The results are similar and a bit stricter to the ones outlined in this paper, possibly stemming from the fact that household-level modelling of default may better capture the interactions between two different mortgages, their LGD's and correlated default.

The single-mortgage hypothetical case is used as a benchmark that is compatible with maximum tolerable risk, and thus is parametrised as a limiting case of the ASN requirements: $\text{LTV}^H = 85\%$, $\text{DSTI}^H \leq 40\%$ and maturity of 30 years. We assume that the hypothetical mortgage has the same underlying collateral, interest rate and other features as the actual secondary loan.

The calibration is carried out at-origination for each actual secondary mortgage, involving the computation of ECL's under two horizons: (a) one year, and (b) lifetime. Lifetime ECL's for household h loan j are defined as:

$$\text{ECL}_h^j := \sum_{t=1}^{n_h^j} \left[\left(1 + i_h^j\right)^{-t} \text{LGD}_{h,t}^j \text{PD}_{h,t}^j \prod_{l=0}^{t-1} \left(1 - \text{PD}_{h,l}^j\right) \right], \qquad j \in \{1, 2; H\},$$

which is practically the same as in equation (7) of Section 3. Note that when we analyse the one-year horizon at origination, we set $n_h^j = 1$, so that the ECL boils down to: $\text{LGD}_{h,1}^j \text{PD}_{h,1}^j$. Generally, $\text{PD}_{h,t}^j$ are one-year-ahead default probabilities, evaluated using the estimated PD model (Table 5). Each loan within a household's two-loan portfolio has a one-year-ahead PD rate that varies over the lifespan of the loan, and is dependent on the household's DSTI, LTV's, maturities, and other metrics:

$$\text{PD}_{h,t}^j = \text{PD}\left(\text{DSTI}_{h,t}, \text{LTV}_{h,t}^j, \text{Maturity}_{h,t}^j, \text{LTV}_{h,t}^{i \neq j}, \mathbb{1}_{\{j=2\}}\right).$$

As we did in earlier exercises, we utilise each mortgage loan's amortisation schedule to compute how its PD and LGD parameters evolve over its lifespan.[40] Rewriting equation (5), LGD parameter is the following:

$$\text{LGD}_{h,t}^j = \text{LGD}\left(\text{LTV}_{h,t}^j | \Delta\right) = \max\left\{ \text{EAD}_{h,t}^j \cdot \left[1 + C - \frac{1 - \Delta}{\text{LTV}_{h,t}^j}\right], \ 0 \right\},$$

where Δ is the assumed decrease in collateral value. One can see from the latter equation that for sufficiently small values of administrative costs C and collateral haircut Δ, and if loan j's cLTV ratio is low, LGD parameter will likely be equal to zero.[41] As in the previous analyses of this paper, LGD is modelled assuming that there is a general decline in home prices under a crisis scenario (downturn LGD). Table 4 tabulates four assumed scenarios that differ in their severity and will be used for this calibration exercise.

The most severe scenario (#4) assumes a house price drop Δ of 30%, which matches

[40] For convenience, we assume a zero probability of recovery/cure from the state of default, since extensive testing indicates that non-zero cure probability does not change the results.

[41] In Section 2 we mentioned that LGD parameters may be positively correlated and thus become larger under the two-mortgage setting. Nonetheless, we are not using this assumption, as we do not have actual LGD data and therefore it is unclear how to model the interaction of both $\left(\text{LGD}_h^1, \ \text{LGD}_h^2\right)$ parameters. If we imposed positive correlation between the two LGD parameters, the calibration results would be even stricter, i.e. requiring even more stringent regulation of secondary mortgages.

Table 4: Assumed macroeconomic scenarios for calibration

Scenario	House price drop – Δ (%)	GDP drop (%)	Change in unemployment rate (p.p.)
#1	−15	−4.1	+5.0
#2	−20	−6.9	+6.4
#3	−25	−8.0	+7.0
#4	**-30**	**-10.7**	**+8.5**

the actual drop that happened in 2009 in Lithuania during the GFC. Although current house price overvaluation measures suggest a relatively modest level of misalignments compared to the situation in the 2000's, we regard the scenario (#4) as baseline for conservative calibration purposes.

By limiting at-origination oLTV^2, a creditor or the regulator will affect the evolution of cLTV^2 and thus LGD^2 over the secondary loan's lifespan. On this basis, for each household that took out a secondary mortgage, we look for a personalised LTV^2 limit that would prevail at loan's origination and thus would equalise (lifetime) ECL's between the actual case, where the household has two mortgages, and the hypothetical case, where the household has only one mortgage loan. Algebraically, we look for $\overline{\mathrm{LTV}}_h^2$ that would solve the following ECL-equating condition:

$$\overline{\mathrm{LTV}}_h^2 \in (0, 85\%) \text{ such that : } \quad \mathrm{ECL}_h^1\left(\mathrm{LTV}_h^1, \overline{\mathrm{LTV}}_h^2\right) + \mathrm{ECL}_h^2\left(\overline{\mathrm{LTV}}_h^2, \mathrm{LTV}_h^1\right) \; = \; \mathrm{ECL}_h^H. \quad (8)$$

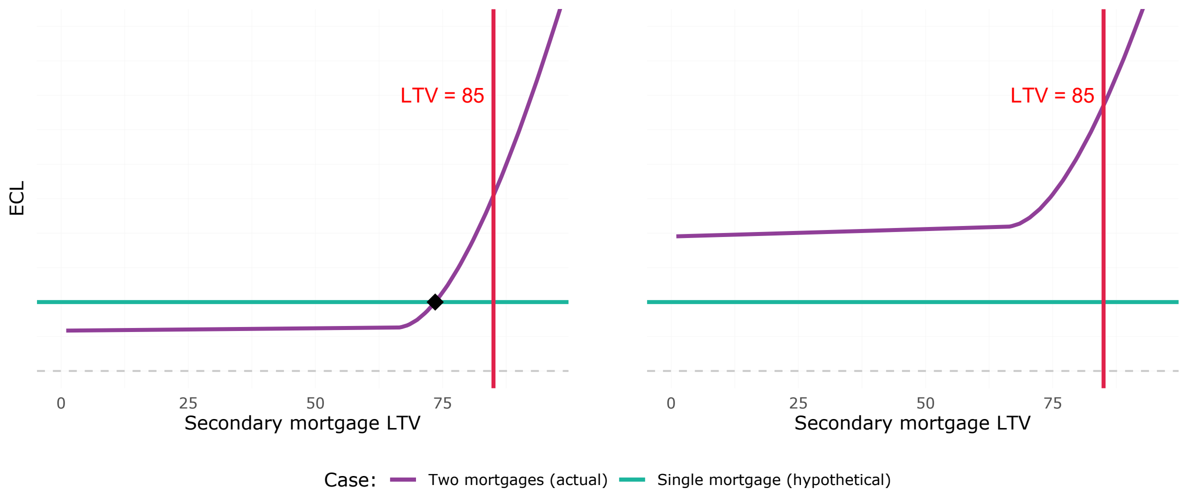
By changing h household's secondary loan oLTV_h^2 ratio, we affect its $\mathrm{PD}_{h,t}^2$ and $\mathrm{LGD}_{h,t}^2$ parameters and therefore the $\mathrm{ECL}_{h,t}^2$. Interestingly, since a secondary loan affects the riskiness of the first loan, any change to oLTV_h^2 will also transmit to the risk parameters of the first mortgage ($\mathrm{PD}_{h,t}^1$, $\mathrm{LGD}_{h,t}^1$, ECL_h^1).[42]

Figure 14 depicts an example of such calibration exercise using actual historical data of two distinct households. One can observe that the purple line, which marks each household's aggregate ECL, is monotonically increasing along with secondary mortgage LTV_h^2 ratio. Interestingly, for both households there is a certain LTV_h^2 level where the ECL_h starts increasing almost exponentially. The point where the ECL of the actual case equals the ECL of the hypothetical single-mortgage case, is deemed as the personalised $\overline{\mathrm{LTV}}_h^2$ limit, which equalises the credit risk between the two cases. The interpretation is that for household (a), 75% is the secondary mortgage LTV ratio, under which the household's mortgage portfolio becomes just as risky as the limiting case of a single-mortgage loan with maximal ASN parameters. Interestingly, based on our solution algorithm, household (b) should not be given a secondary loan as its aggregate two-mortgage credit risk is globally higher than the single-mortgage case. This may be associated with already high DSTI_b or LTV_b^1 ratios, and overall high risk of this particular household.

[42] Computationally, for each household h we look for an $\overline{\mathrm{LTV}}_h^2$ that would solve the highly nonlinear equation (8), taking into account the entire amortisation scheme of each loan $j \in \{1, 2; H\}$, and their interaction through the common DSTI_h ratio and other metrics.

Figure 14: Example of LTV^2 calibration: two households

(a) solution is found – eligible borrower (b) solution is not found – ineligible borrower



Notes: based on assumptions of lifetime ECL and $\Delta = 30\%$, purple and green curves mark households' ECL's depending on the LTV^2_h ratio. (a) contains an actual household for whom the calibration found a solution $\overline{\text{LTV}}^2_a > 0$ – the purple curve crosses the green line in $\overline{\text{LTV}}^2_a \in (0, 85)$ domain; (b) actual household for whom no LTV^2_b can equalise the credit risk to the hypothetical case of a single mortgage, therefore the secondary loan should not be granted.

5.2.2 Calibration results

Given that we outlined the micro-calibration method, now we turn to discuss the results of the exercise under one-year and lifetime settings.

(a) One-year horizon

Under the one-year setting we assume: $n^j_h = 1,\ \forall j \in \{1, 2; H\}$, thus we analyse the ECL one year after the initiation of each secondary loan. The calibration exercise involved finding personalised $\overline{\text{LTV}}^2_h$ limits for around 6 th. households who took out secondary loans throughout 2012-2019. Remarkably, 1.5 th. or a quarter of the analysed households should not have been granted a secondary mortgage, as the calibration algorithm did not find a solution within the domain of $\overline{\text{LTV}}^2_h \in (0, 85\%)$. In plain words, their two-mortgage ECL exceeded that of a single hypothetical mortgage, irrespectively of LTV^2_h, as in the example of Figure 14(b).

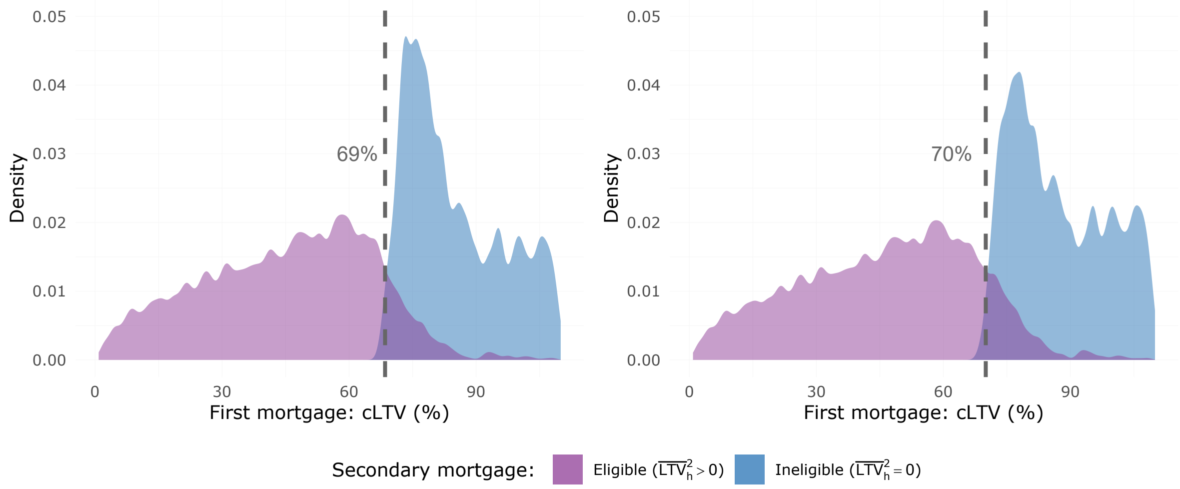
What is interesting, many of the households who should not have been eligible to receive a secondary loan, had their first loan LTV^1_h ratios above 70%. This situation is depicted in Figure 15(a), where one can see that the majority of households who had $\text{LTV}^1_h < 70\%$ were eligible as suggested by our calibration algorithm.[43]

Now we turn to analyse the resulting personalised $\overline{\text{LTV}}^2_h$ limits. We assume that each

[43] Please not that this threshold $\text{LTV}^1_h < 70\%$ is highly dependent on the assumed Δ house price drop, which in our baseline case is 30%. For instance, if we assumed $\Delta = 15\%$, then LTV^1_h threshold would be around 85%.

Figure 15: Relationship between LTV_h^1 distribution and eligibility for secondary loan

(a) one-year horizon (b) lifetime horizon



Notes: based on assumption of $\Delta = 30\%$. A household h is eligible to receive a secondary mortgage, if calibrated $\overline{\mathrm{LTV}}_h^2 > 0$; and ineligible, if $\overline{\mathrm{LTV}}_h^2 = 0$. Grey dashed vertical lines mark first mortgage LTV_h^1 threshold as evaluated using the depicted density functions.

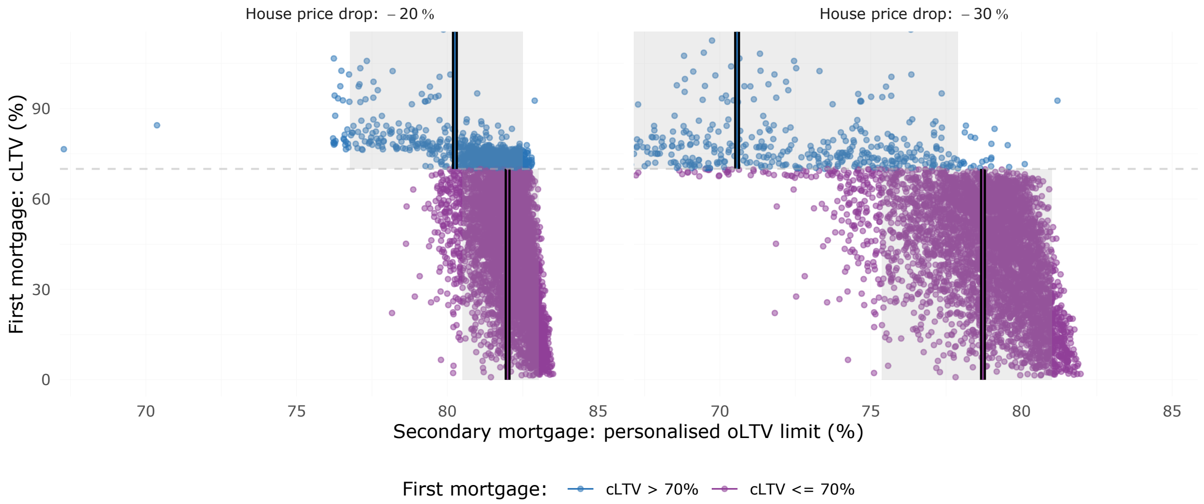
creditor assesses the creditworthiness of each applicant household, and decides whether the secondary mortgage could be granted. On this basis, in our calibration setting, we restrict our attention to the subsample of households who, according to the algorithm solution, were eligible receivers of secondary mortgages, i.e. $\overline{\mathrm{LTV}}_h^2 > 0$ – a truncated set.

The calibration results under the one-year horizon setting are depicted in scatterplots of Figure 16(a), which are based on the assumed house price drop (Δ). Each point in the chart represents a combination of the personalised $\overline{\mathrm{LTV}}_h^2$ limit (x-axis) for each household, and the corresponding first mortgage actual LTV_h^1 ratio (y-axis). Additionally, we split all households into two sets, based on the first mortgage threshold obtained from Figure 15: $\mathrm{LTV}_h^1 \leq 70\%$ – those who have well collateralised first mortgages, and $\mathrm{LTV}_h^1 > 70\%$ – those who have highly leveraged first loans. For each of the two subsets of households, we compute average secondary mortgage $\overline{\mathrm{LTV}}^2$ limits – vertical lines, and respective 90% confidence intervals – lightgrey rectangles. The resulting personalised calibration aggregate estimates are tabulated just below Figure 16.

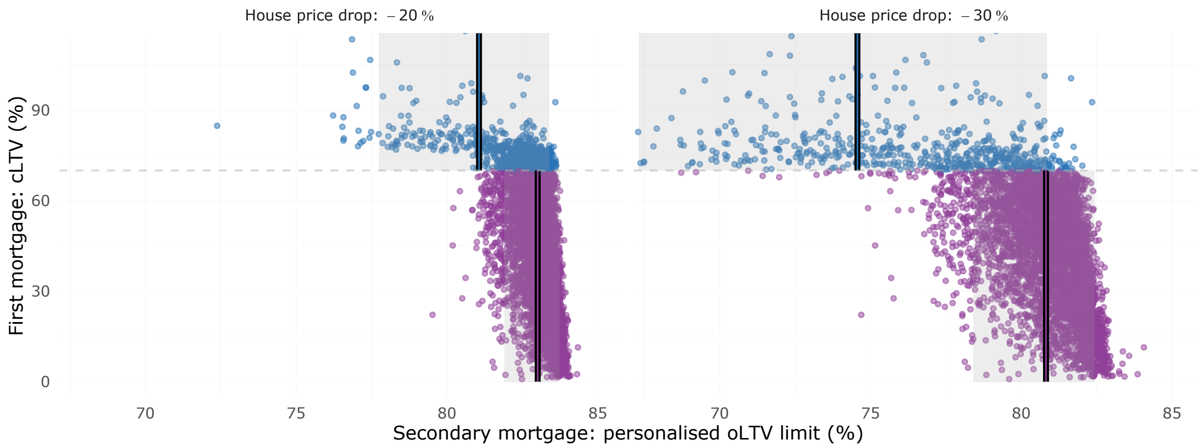
Calibration results suggest that, indeed, secondary mortgages do need to have an LTV that is strictly lower than the headline LTV limit, as all points are positioned to the left of 85%. This had been the case even before February 1, 2022 when the new regulation was enacted.

Figure 16: Personalised calibration of $\overline{\text{LTV}}_h^2$ limit

(a) one-year horizon



(b) lifetime horizon



	Calibrated $\overline{\text{LTV}}^2$ limit: means and 90% confidence intervals							
	(a) one-year horizon				(b) lifetime horizon			
House price drop	**−15%**	**−20%**	**−25%**	**−30%**	**−15%**	**−20%**	**−25%**	**−30%**
$\text{cLTV}^1 > 70$	83 [82, 84]	80 [77, 82]	74 [71, 81]	70 [66, 78]	83 [83, 84]	81 [78, 83]	78 [73, 82]	75 [67, 81]
$\text{cLTV}^1 \in (0, 70]$	84 [83, 84]	82 [80, 83]	80 [78, 82]	79 [75, 81]	84 [83, 84]	83 [82, 84]	82 [80, 83]	81 [78, 82]
$\text{cLTV}^1 > 0$	84 [83, 84]	82 [80, 83]	80 [76, 82]	78 [72, 81]	84 [83, 84]	83 [81, 84]	81 [78, 83]	80 [75, 82]

Notes: the chart maps a relationship between the personalised $\overline{\text{LTV}}_h^2$ limits and corresponding first loan LTV_h^1 ratios, using different calibration horizons. Vertical lines denote the averaged $\overline{\text{LTV}}^2$ limits with lightgrey rectangle areas being the 90% confidence intervals. The table below shows aggregate calibration results that are based on different horizons and house price drop (Δ) assumptions, by different subsets of households (by LTV_h^1).

There is a clear negative relationship between the LTV_h^1 ratio of the first mortgage loan and the corresponding personalised secondary mortgage $\overline{\text{LTV}}_h^2$ limit. Essentially, borrowers with still active and relatively unamortised loans could be issued secondary loans with relatively small LTV^2 ratio and hence a higher down payment. Moreover, the relationship between LTV_h^1 and $\overline{\text{LTV}}_h^2$ is highly nonlinear as characterised by the kink around $\text{LTV}_h^1 \approx 70\%$, which corresponds to the same threshold obtained from Figure 15(a). Many households with $\text{LTV}_h^1 > 70\%$ may be eligible for a secondary mortgage, however, with on average low personalised $\overline{\text{LTV}}_h^2$ limit of 70%. Households whose first mortgage is largely amortised ($\text{LTV}_h^1 < 70\%$) may borrow with an $\overline{\text{LTV}}^2$ ratio of up to 80%.

The overall tightness of the general LTV^2 limit depends on the assumed house price drop scenario. For instance, under a less severe fall in house prices ($\Delta = 15\%$), the secondary LTV^2 limit should be situated around 83-84%. In general, the assumed magnitude of house price decline (Δ) could be based on historical volatility of the local housing market, current level of misalignments, and overall risk tolerance by the regulator. As previously discussed, 30% drop in house prices, or scenario (#4), is assumed as our baseline, based on Lithuania's experience during the GFC and recent dynamics of the housing market.

(b) Lifetime horizon

Instead of analysing only the one-year period after initiation of secondary mortgages, we now move to the calibration under the lifetime horizon setting. The calibration results are remarkably similar to the previous (a) setting. Out of 6 th. households with secondary mortgages, around 1.3 th., or one-fifth, should not have received a loan, i.e. their personalised $\overline{\text{LTV}}_h^2$ limits are zero. As in one-year setting panel (a), panel (b) of Figure 15 depicts a strong relationship between eligibility of receiving a secondary mortgage and first mortgage LTV_h^1 ratio, with $\text{LTV}_h^1 = 70\%$ being the threshold.

The exact personalised $\overline{\text{LTV}}_h^2$ (> 0) limits along with corresponding predecessor-mortgage LTV_h^1 ratios are depicted in Figure 16(b). Again, we can see that all points have $\overline{\text{LTV}}_h^2 <$ 85%, and that there is a strong kinked relationship with first mortgage LTV_h^1 ratio, which also depends on the magnitude of the decline in home prices (Δ).

Although lifetime horizon calibration results are qualitatively similar, they are a bit less stringent compared to those when using the one-year horizon. This can be seen by comparing (a) and (b) subplots in Figure 16, and inspecting the tabulated aggregate limits just below the charts. Under the baseline fall in house prices ($\Delta = 30\%$), average $\overline{\text{LTV}}^2$ limit for households with $\text{LTV}^1 > 70\%$ is equal to 75% under the lifetime setting, wherein the one-year setting it is around 70%. Nonetheless, the 90% confidence intervals of [66, 78] and [67, 81] are largely overlapping and distant from the headline limit of 85%.

Calibration under the lifetime horizon setting results in milder secondary mortgage LTV limits what may be surprising. Nevertheless, the difference can be explained by the fact that the one-year setting (a) does not fully take into account the residual maturity of first mortgage loan. More concretely, over the secondary loan's lifespan, there will be a significant amount of time when both loans coexist. However, if the first loan's residual maturity is short-spanned, the secondary loan will be effectively single throughout most of its own lifetime. While the lifetime horizon setting takes into account this amortisation schedule feature, the one-year setting does not, thus produces the more stringent calibration results.

To summarise, our baseline micro-calibration results suggest the following finding:

Finding 7 *To compensate for the elevated default probability of secondary mortgages, their regulatory LTV limit should be: a) strictly lower than the headline LTV limit of 85%; b) differentiated by the borrower's first mortgage LTV – whether it is below or above 70%.*

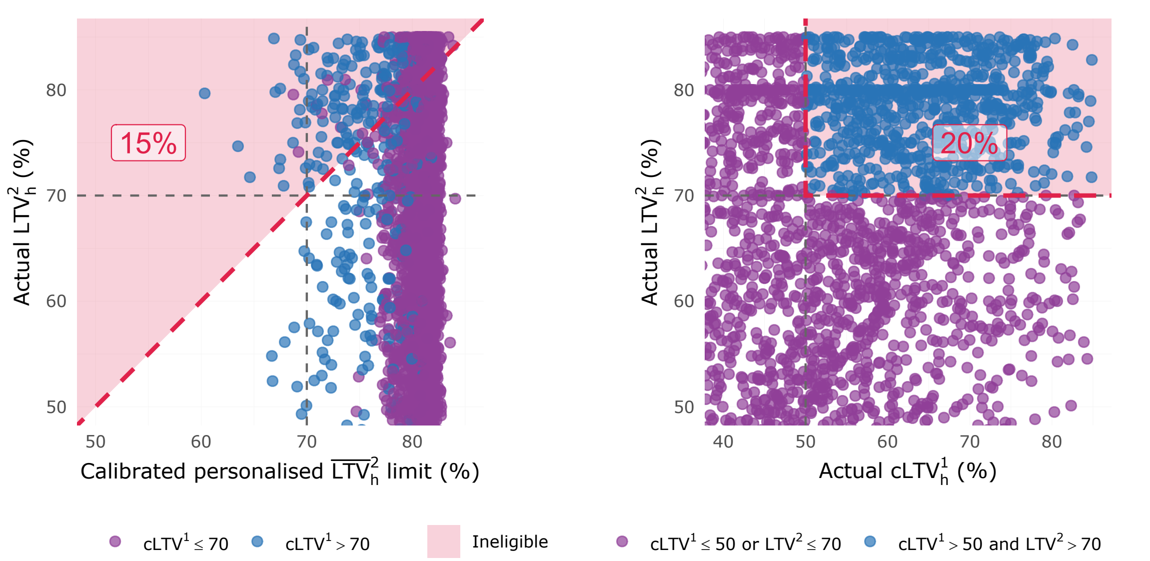
5.3 Final remarks on secondary mortgage LTV regulation

Our previous analysis of Section 2 suggests that secondary mortgages were historically issued with relatively high LTV ratios, often at least 80%. This is at odds with the fact that their lifetime PD rates are significantly higher than those of single loans. Also, mere issuance of a secondary mortgage does make the corresponding first loan riskier.

Now that we have historical data of secondary mortgage issuance, we can compare their actual LTV ratios to those resulting from our calibration exercise, as graphed in Figure 17(a). One can immediately see that the positive correlation between the actual

Figure 17: Counterfactual impact on secondary loan issuance in 2012-2019

(a) Calibrated personal limit and actual LTV_h^2 ratio (b) Current regulation and actual LTV_h^1 and LTV_h^2 ratios



Notes: the personalised $\overline{\mathrm{LTV}}_h^2$ limits are based on calibration that assumed lifetime ECL's and $\Delta = 30\%$. The actual LTV_h^1, LTV_h^2 are based on real historical data of multiple-mortgage households.
(a) the 45° red angle represents the situation, where the actual LTV_h^2 is equal to the calibrated $\overline{\mathrm{LTV}}_h^2$ limit. All loan-points above that line, in the red triangle, could be deemed having LTV ratios that were too high compared to the calibrated values; (b) the red rectangular area marks the loan-points which either should not have been granted, or were issued with too high LTV ratios, if current regulation was present throughout 2012-2019.

LTV ratio and calibrated values is lacking. In many cases borrowers took out secondary mortgages to finance their additional house purchases with LTV's that were relatively low. This is either because of relatively stringent personal limits imposed by the credit institution, or personal selection of debt-equity mixture by the borrowers. What is more revealing, there are around 15% of all secondary mortgages that should have been issued with lower LTV ratios compared to the calibrated personalised limits, as represented by the red triangular area above the 45° angle.

What is more, panel (b) of Figure 17 reveals that there was no correlation between the actual secondary loan LTV ratio and corresponding first mortgage cLTV ratio. We observe that many borrowers took out secondary mortgages with high LTV rates, even when their first mortgages were relatively unamortised with LTV rates above 70%. In fact, the red rectangular area represents around 20% of loans that throughout 2012-2019 were granted with too high LTV ratios, compared to the new regulation of 2022.

Based on these tendencies and recent emergance of secondary mortgages, we deem that the market either has different and perhaps more detailed information on borrower-loan characteristics, or different risk appetite, or simply fails to internalise the inherent risks associated with secondary mortgage issuance. While our loan database may have discrepancies and errors, we base our analysis on all mortgage information submitted by multiple lenders, and hence have a relatively good picture of the market, including household information on income and family composition.

Regarding the risk appetite, we acknowledge the fact that our objective function in equation (8) may be rather restrictive, since it compares the ECL's of two loans with a single hypothetical mortgage. To tackle that, we implemented an alternative calibration exercise with a more lax objective function of:

$$\mathrm{ECL}_h^2\left(\overline{\mathrm{LTV}}_h^2, \mathrm{LTV}_h^1\right) \;=\; \mathrm{ECL}_h^H.$$

In essence, we equivalised the ECL of only the secondary loan to the hypothetical single-mortgage case for a farer comparison. The calibration results that are depicted in Figure 18 of Appendix A suggest of milder secondary LTV limits nearing 80%, which are more in line with the observed market practice. However, we deem this approach as inferior to our baseline calibration based on equation (8), since it does not take into account the imposed negative externality on the first mortgage loan in terms of heightened credit risk. That is why under the alternative approach there is no clear negative relationship between first mortgage LTV and the calibrated secondary mortgage LTV limit, as can be seen from the table below Figure 18.

Therefore, the potential market failure to mitigate secondary mortgage risks should be addressed with restrictive regulation, as done by the Bank of Lithuania and regulators in other countries, including Belgium, Ireland, Norway, etc. Other countries including Finland, Iceland or Luxembourg implicitly have similar regulation, whereby exemptions are made for first-time buyers, rather than explicitly restricting investors.

Although our baseline calibration results suggest that secondary mortgage LTV limit should be around 75% [67, 81] with first mortgage LTV threshold of 70%, Bank of Lithuania enacted a bit tighter regulation of 70% LTV limit with 50% first mortgage threshold. While the 70% secondary mortgage LTV limit is within the lower end of our estimated confidence interval, the threshold limit of 50% is significantly lower than 70%, which was suggested by our model. Nonetheless, this discrepancy could be explained by the fact that our calibration approach merely takes into account the micro-level credit risk, with no regard for the possible wider impact of secondary mortgages on the housing credit market and stability of the general economy. As discussed in Section 2, secondary mortgages may exhibit negative externalities on the whole housing market as they tend to by highly procyclical and more risky. Furthermore, since secondary housing loans add undesirable pressure to formation of imbalances, they may amplify the negative social side effects of BBM regulation on first-time buyers and young families.

To conclude this section, in addition to Kelly and O'Toole (2018) who find multiple-loan borrowers to default more often, our findings are also supported by the agent-based models of Baptista et al. (2016) and Tarne et al. (2022). The latter two papers find that buy-to-let investors, who presumably take out secondary mortgages, amplify credit-housing cycles. In particular, Tarne et al. (2022) showed that if regulators reduced investors' access to credit, they could alleviate wealth inequality and reduce consumption volatility. The latter paper finds it important to apply differentiated BBM's to different classes of borrowers, primarily restricting credit for buy-to-let investors.

6 Conclusions

Although policymakers should not seek to change BBM policy frequently, one cannot rule out an occasional recalibration of instruments, especially when data is suggesting that existing regulation may be insufficient. In response to recent dynamism of credit and housing markets, this paper attempted to take a second look at the ASN framework in Lithuania. Assessment of BBM parametrisation was carried out by modelling mortgage-level credit risk throughout each household loan's lifespan, involving the estimation of PD and LGD parameters. Our model findings mainly focus on three topics within the realm of BBM regulation.

One is the efficacy of overall BBM framework, which we find effective in significantly reducing credit risk of individual and aggregate nature, so that banking portfolio is now much more resilient to adverse shocks compared to the situation preceding the introduction of ASN regulation. By the same token, had ASN limits been imposed in the 2000's, Lithuanian banking sector losses would have likely been minimal during the GFC.

Two is the adequacy of ASN parametrisation, which can be questioned in light of recent emergence of housing credit misalignments. While the headline LTV requirement of 85% is relatively stringent with no exemptions for first time buyers, we see some room in further tightening of the DSTI cap and maturity limit. The nonlinear nature of our modelling results show that limits on DSTI and stressed DSTI may have been on the loose end. Taking into account that any reduction in the DSTI cap would invoke households to take out loans with longer maturities, our analysis suggests of a joint tightening in the stressed DSTI cap and maturity limit. The combined action would allow the regulator to achieve the desired policy effectiveness in terms of reduced flow of credit, while minimising lifetime credit risk of housing loans.

Notwithstanding, since our training dataset spans the low-rate environment, the analysis and hence the latter recommendation does not account for the rapid reversal of monetary policy stance that resulted in rising base rates which are nearing 3% at the time of writing this paper. Early data shows that upper percentiles of the DSTI distribution are slowly approaching the BBM limit of 40%, suggesting that the pace of credit growth could slow down, and that the credit overflow gap may be contained, if not closed. Monetary policy is known to have long time lags, therefore any rash tightening of BBM's could be harmful.

Three is secondary and subsequent mortgages, which have been quite prevalent since the onset of the Covid-19 pandemic. Historical procyclicality of secondary mortgage issuance suggests of a market failure to internalise the inherent risk of this asset class that needs to be addressed by regulation. Secondary mortgages have a substantially higher chance of default over their lifespans than single mortgage loans, and in addition to that, their issuance increases the credit risk of existing housing loans. The additional risk of secondary mortgages rightly is and should remain suppressed by the imposed tighter LTV requirement to keep their credit risk in line with single mortgage loans.

The decision to set the secondary mortgage LTV limit to 70% by the Bank of Lithuania addresses both high individual credit risk of secondary mortgages, and also the negative externalities that this asset class imposes on other market participants and the general economy. The full effectiveness of this new regulation remains to be seen, however, there had already been some signs of moderation in secondary mortgage flows even before the rise in interest rates.

The fact that we assess micro-level credit risk is surely a strength but also the main weakness of our analytical framework. On one hand, granular loan data allows to evaluate BBM instruments with precision by looking at different market segments, utilising variation across loans and borrowers, matching it with their income. On the other hand, reliance on metrics that measure individual credit risk can give an incomplete picture, as the framework does not capture various feedback loops and negative externalities of wider scale and of macroprudential interest.

To address this issue, the analysis could be expanded for a more systemic approach that incorporates not only data on loans, but also the banking sector and the rest of the economy. One alternative would be to replace the survey-based setting with our loan-level lifetime credit risk framework in the micro-macro setup of Gross and Población (2017). Another, yet more ambitious, idea would be to build a semi-structural framework bearing similarities to the model of Budnik et al. (2020), containing a fully-fledged banking sector and a macroeconomic block, possibly allowing to capture spillover effects between the mortgage market and the rest of the economy.

Lastly, the analysis of this paper was done at the cusp of changing monetary policy stance, and using low-interest rate environment data. Rapidly changing interest rates combined with eroding purchasing power may pose new challenges for borrowers, therefore additional variation in default data may suggest different conclusions regarding the appropriateness of the DSTI and stressed DSTI measures. These insights could be a basis for forming a new kind of macroprudential policy that is contingent on monetary policy stance.

References

Acharya, V. V., Bergant, K., Crosignani, M., Eisert, T., and McCann, F. (2022). The Anatomy of the Transmission of Macroprudential Policies. *The Journal of Finance*, 77(5):2533–2575.

Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M., Nier, E., and Wang, N. (2019). Digging Deeper–Evidence on the Effects of Macroprudential Policies from a New Database. IMF Working Papers 2019/066, International Monetary Fund.

Ampudia, M., Lo Duca, M., Farkas, M., Perez-Quiros, G., Pirovano, M., Rünstler, G., and Tereanu, E. (2021). On the effectiveness of macroprudential policy. Working Paper Series 2559, European Central Bank.

Andries, A. M., Copaciu, A., Popa, R., and Vlahu, R. (2021). Recourse and (strategic) mortgage defaults: Evidence from changes in housing market laws. Working Papers 727, De Nederlandsche Bank.

Araujo, J., Patnam, M., Popescu, A., Valencia, F., and Yao, W. (2020). Effects of Macroprudential Policy: Evidence from Over 6,000 Estimates. IMF Working Papers 2020/067, International Monetary Fund.

Baptista, R., Farmer, J. D., Hinterschweiger, M., Low, K., Tang, D., and Uluc, A. (2016). Macroprudential policy in an agent-based model of the UK housing market. Working papers 619, Bank of England.

Baudino, P., Lielkalne, O., Reichenbachas, T., Tamm, M., and Vrbaski, R. (2022). The 2008 financial crises in the Baltic countries. FSI Crisis Management Series No 3, Financial Stability Institute, Bank for International Settlements.

Brandao-Marques, L., Gelos, G., Narita, M., and Nier, E. (2020). Leaning Against the Wind: A Cost-Benefit Analysis for an Integrated Policy Framework. Working Papers 2020/123, International Monetary Fund.

Bruneau, G., Christensen, I., and Meh, C. (2018). Housing market dynamics and macroprudential policies. *The Canadian Journal of Economics / Revue canadienne d'Economique*, 51(3):864–900.

Brzoza-Brzezina, M., Gelain, P., and Kolasa, M. (2014). Monetary and macroprudential policy with multiperiod loans. NBP Working Paper No. 192, Narodowy Bank Polski.

Budnik, K., Balatti, M., Dimitrov, I., Groß, J., Kleemann, M., Reichenbachas, T., Sanna, F., Sarychev, A., Siņenko, N., and Volk, M. (2020). Banking euro area stress test model. Working Paper Series 2469, European Central Bank.

Buesa, A., Población García, F. J., and Tarancón, J. (2019). Measuring the procyclicality of impairment accounting regimes: a comparison between IFRS 9 and US GAAP. Working Paper Series 2347, European Central Bank.

Catapano, G., Franceschi, F., Michelangeli, V., and Loberto, M. (2021). Macroprudential Policy Analysis via an Agent Based Model of the Real Estate Sector. Temi di discussione (Economic working papers) 1338, Bank of Italy.

Cerutti, E., Claessens, S., and Laeven, L. (2017). The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability*, 28(C):203–224.

Clerc, L., Derviz, A., Mendicino, C., Moyen, S., Nikolov, K., Stracca, L., Suarez, J., and Vardoulakis, A. P. (2015). Capital Regulation in a Macroeconomic Model with Three Layers of Default. *International Journal of Central Banking*, 15(3):9–63.

Cokayne, G. (2019). The effects of macroprudential policies on house price cycles in an agent-based model of the Danish housing market. Working Papers 138, Danmarks Nationalbank.

Darracq Pariès, M., Kok Sørensen, C., and Rodriguez-Palenzuela, D. (2011). Macroeconomic propagation under different regulatory regimes: Evidence from an estimated DSGE model for the Euro Area. *International Journal of Central Banking*, 7(4):49–113.

de Haan, L. and Mastrogiacomo, M. (2020). Loan to Value Caps and Government-Backed Mortgage Insurance: Loan-Level Evidence from Dutch Residential Mortgages. *De Economist*, 168(4):453–473.

Ferrero, A., Harrison, R., and Nelson, B. (2022). House price dynamics, optimal LTV limits and the liquidity trap. Staff Working Paper No. 969, Bank of England.

Forlati, C. and Lambertini, L. (2011). Risky mortgages in a DSGE model. *International Journal of Central Banking*, 7(1):285–335.

Gaffney, E., Kelly, R., and McCann, F. (2014). A transitions-based framework for estimating expected credit losses. Research Technical Papers 16/RT/14, Central Bank of Ireland.

Galán, J. E. and Lamas, M. (2019). Beyond the LTV ratio: new macroprudential lessons from Spain. Working Papers 1931, Banco de España.

Gatt, W. (2021). Housing boom-bust cycles and asymmetric macroprudential policy. Mimeo, accepted at Journal of Money, Credit and Banking.

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*, 61:510–528.

Jurča, P., Klacso, J., Tereanu, E., Forletta, M., and Gross, M. (2020). The Effectiveness of Borrower-Based Macroprudential Measures: A Quantitative Analysis for Slovakia. IMF Working Papers 2020/134, International Monetary Fund.

Karmelavičius, J. (2021). Risky Mortgages and Macroprudential Policy: A Calibrated DSGE Model for Lithuania. *Ekonomika*, 100(2):6–39.

Karmelavičius, J., Mikaliūnaitė-Jouvanceau, I., and Buteikis, A. (2022a). What drove the rise in bank lending rates in Lithuania during the low-rate era? Occasional Paper Series No. 43/2022, Bank of Lithuania.

Karmelavičius, J., Mikaliūnaitė-Jouvanceau, I., and Petrokaitė, A. (2022b). Housing and credit misalignments in a two-market disequilibrium model. Occasional Paper Series No. 42/2022, Bank of Lithuania.

Kelly, R., O'Malley, T., and O'Toole, C. (2015). Designing Macro-prudential Policy in Mortgage Lending: Do First Time Buyers Default Less? Research Technical Papers 02/RT/15, Central Bank of Ireland.

Kelly, R. and O'Toole, C. (2018). Mortgage default, lending conditions and macroprudential policy: Loan-level evidence from UK buy-to-lets. *Journal of Financial Stability*, 36(C):322–335.

Kukk, M. (2021). What are the triggers for arrears on debt over a business cycle? Evidence from panel data. *International Journal of Finance & Economics*, page 1–23.

Kulikauskas, D. (2016). Fundamental housing prices in the Baltic States: empirical approach. *Baltic Journal of Economics*, 16(2):53–80.

Kuodis, R. and Ramanauskas, T. (2009). From boom to bust: lessons from Lithuania. *Pinigų studijos*, 1:96–104.

Laliotis, D., Buesa, A., Leber, M., and Población, J. (2020). An agent-based model for the assessment of LTV caps. *Quantitative Finance*, 20(10):1721–1748.

Lambertini, L., Mendicino, C., and Teresa Punzi, M. (2013). Leaning against boom–bust cycles in credit and housing prices. *Journal of Economic Dynamics and Control*, 37(8):1500–1522.

Lim, C., Columba, F., Costa, A., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T., and Wu, X. (2011). Macroprudential Policy: What Instruments and How to Use them? Lessons From Country Experiences. IMF Working Papers 2011/238, International Monetary Fund.

Malovaná, S., Hodula, M., Gric, Z., and Bajzík, J. (2022). Borrower-Based Macroprudential Measures and Credit Growth: How Biased is the Existing Literature? Working Paper Series 08/2022, Czech National Bank.

Mandrekar, J. N. (2010). Receiver operating characteristic curve in diagnostic test assessment. *Journal of Thoracic Oncology*, 5(9):1315–1316.

Matkėnaitė, S., Ramanauskas, T., and Reichenbachas, T. (2016). Paskolos ir užstato vertės santykio ribojimo Lietuvoje ekonominiai aspektai. Occasional Paper Series No. 9/2022, Bank of Lithuania.

Mendicino, C. (2012). Collateral Requirements: Macroeconomic Fluctuations and Macro-Prudential Policy. Working Papers 201211, Banco de Portugal.

Mendicino, C. and Punzi, M. T. (2014). House prices, capital inflows and macroprudential policy. *Journal of Banking & Finance*, 49(C):337–355.

Mihai, I., Popa, R., and Banu, E. (2018). The probability of default for private individuals using microeconomic data. What is the role played by macroprudential measures? Mimeo.

Neugebauer, K., Oliveira, V., and Ângelo Ramos (2021). Assessing the effectiveness of the Portuguese borrower-based measure in the Covid-19 context. Working Papers 202110, Banco de Portugal.

Nier, E., Popa, R., Shamloo, M., and Voinea, L. (2019). Debt Service and Default: Calibrating Macroprudential Policy Using Micro Data. IMF Working Papers 2019/182, International Monetary Fund.

Nookhwun, N. and Tsomocos, D. (2017). Mortgage default, financial disintermediation and macroprudential policies. Mimeo.

Poghosyan, T. (2019). How Effective is Macroprudential Policy? Evidence from Lending Restriction Measures in EU Countries. Working Papers 2019/045, International Monetary Fund.

Ramanauskas, T. (2005). Bankų kredito didėjimas makroekonominiu požiūriu (Assessment of Bank Credit Growth from Macroeconomic Perspective). *Pinigų studijos*, 5:78–97.

Ramanauskas, T. (2011). What Caused the Recent Boom-And-Bust Cycle in Lithuania? Evidence from a Macromodel with the Financial Sector. Working Paper Series 10, Bank of Lithuania.

Reichenbachas, T. (2020). Assessing the impact of macroprudential measures: The case of the LTV limit in Lithuania. Working Paper Series No. 80/2020, Bank of Lithuania.

Richter, B., Schularick, M., and Shim, I. (2019). The costs of macroprudential policy. *Journal of International Economics*, 118:263–282.

Rubio, M. and Carrasco-Gallego, J. A. (2014). Macroprudential and monetary policies: Implications for financial stability and welfare. *Journal of Banking & Finance*, 49:326–336.

Rubio, M. and Comunale, M. (2016). Lithuania in the Euro Area: Monetary Transmission and Macroprudential Policies. Working Paper Series 34, Bank of Lithuania.

Rutkauskas, V., Kulikauskas, D., and Šumskis, V. (2015). Lietuvos namų ūkių finansinė būklė ir finansų sistemos stabilumas (Financial soundness of Lithuanian households and the stability of the financial sector). *Pinigų studijos*, 2:63–73.

Tarne, R., Bezemer, D., and Theobald, T. (2022). The effect of borrower-specific loan-to-value policies on household debt, wealth inequality and consumption volatility: An agent-based analysis. *Journal of Economic Dynamics and Control*, 144:104526.

Tzur-Ilan, N. (2020). The Real Consequences of LTV Limits on Housing Choices. Mimeo.

A Tables and figures

Table 5: One-year-ahead PD estimation results: *full* model

	Model 1 (baseline)	Model 2	Model 3
Borrower and loan features			
(Intercept)	$-$**7.08** (0.21)***	$-$**7.10** (0.21)***	$-$**7.07** (0.21)***
Residual maturity	**0.01** (0.00)***	**0.01** (0.00)***	**0.01** (0.00)***
Has interest rate	0.25 (0.20)	0.26 (0.20)	0.19 (0.20)
Interest rate	**0.08** (0.00)***	**0.09** (0.00)***	**0.09** (0.00)***
Secondary mortgage (chron.)	0.05 (0.01)***	0.06 (0.01)***	0.06 (0.01)***
Has other mortgages	0.13 (0.01)***	0.13 (0.01)***	**0.14** (0.01)***
Has other mort.:Other mortgages cLTV	**0.00** (0.00)***	**0.00** (0.00)***	**0.00** (0.00)***
Adults and HH members ratio	$-$0.10 (0.02)***	$-$0.10 (0.02)***	$-$0.09 (0.02)***
Income not reported	**2.01** (0.05)***	**2.01** (0.05)***	**2.00** (0.05)***
Income group 1	**1.77** (0.04)***	**1.77** (0.04)***	**1.77** (0.04)***
Income group 2	**1.16** (0.04)***	**1.17** (0.04)***	**1.16** (0.04)***
Income group 3	**0.50** (0.05)***	**0.50** (0.05)***	**0.49** (0.05)***
HH credit history (3 years)	**2.52** (0.01)***	**2.52** (0.01)***	**2.55** (0.01)***
Loan is delinquent for (60, 90) d.	**2.87** (0.02)***	**2.87** (0.02)***	**2.88** (0.02)***
Macroeconomic variables			
Annual real GDP growth	$-$0.02 (0.01)*	$-$0.02 (0.01)*	$-$0.02 (0.01)*
Unemployment rate	**0.04** (0.00)***	**0.04** (0.00)***	**0.04** (0.00)***
Annual inflation	0.04 (0.00)***	0.04 (0.00)***	0.04 (0.00)***
Borrower-based measures			
Has oLTV	$-$**1.21** (0.02)***	$-$**1.21** (0.02)***	$-$**1.21** (0.02)***
oLTV	**0.00** (0.00)***	**0.00** (0.00)***	**0.00** (0.00)***
Has oDSTI	$-$**0.82** (0.05)***		
oDSTI cub1	**0.70** (0.03)***		
oDSTI cub2	**0.96** (0.10)***		
oDSTI cub3	**0.73** (0.02)***		
Has oDSTI*		$-$**0.68** (0.05)***	
oDSTI* cub1		**0.61** (0.03)***	
oDSTI* cub2		0.67 (0.10)***	
oDSTI* cub3		**0.65** (0.02)***	
Has oDTI			$-$**0.73** (0.04)***
oDTI cub1			**0.71** (0.02)***
oDTI cub2			**1.15** (0.07)***
oDTI cub3			**0.73** (0.02)***
Origination time dummies	YES	YES	YES
Bank dummies	YES	YES	YES
Household economic activity	YES	YES	YES
Observations	4,842,974	4,842,974	4,842,974
AUROC	0.9052	0.9050	0.9038

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Coefficients in bold have p-values lower than 10^{-20}.

Terms oD(S)TI$^{(*)}$ cub1-3 refer to cubic spline polynomials, as in Mihai et al. (2018).

Table 6: One-year-ahead PD estimation results: *full* model ($c\cdot$ – current)

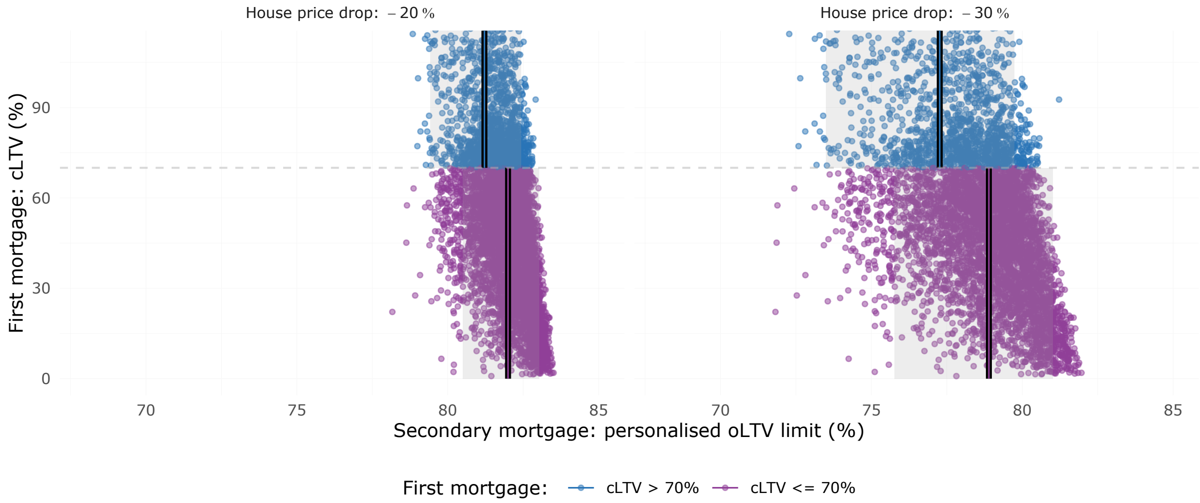
	Model 1	Model 2
Borrower and loan features		
(Intercept)	$\mathbf{-6.49}$ (0.21)***	$\mathbf{-6.49}$ (0.21)***
Residual maturity	**0.01** (0.00)***	**0.01** (0.00)***
Has interest rate	0.40 (0.20)*	0.39 (0.20)
Interest rate	**0.08** (0.00)***	**0.09** (0.00)***
Secondary mortgage (chron.)	0.09 (0.01)***	0.11 (0.01)***
Has other mortgages	0.07 (0.01)***	0.08 (0.01)***
Has other mort.:Other mortgages cLTV	**0.00** (0.00)***	**0.00** (0.00)***
Adults and HH members ratio	-0.11 (0.02)***	-0.10 (0.02)***
Income not reported	**1.29** (0.05)***	**1.28** (0.05)***
Income group 1	**1.24** (0.04)***	**1.24** (0.04)***
Income group 2	**0.86** (0.04)***	**0.86** (0.04)***
Income group 3	0.38 (0.05)***	0.37 (0.05)***
HH credit history (3 years)	**2.44** (0.01)***	**2.45** (0.01)***
Loan is delinquent for (60, 90) d.	**2.83** (0.02)***	**2.83** (0.02)***
Macroeconomic variables		
Annual real GDP growth	-0.02 (0.01)*	-0.02 (0.01)*
Unemployment rate	**0.03** (0.00)***	**0.03** (0.00)***
Annual inflation	0.03 (0.00)***	0.03 (0.00)***
Borrower-based measures		
Has oLTV	$\mathbf{-1.24}$ (0.02)***	$\mathbf{-1.23}$ (0.02)***
oLTV	**0.00** (0.00)***	**0.00** (0.00)***
Has cDSTI	$\mathbf{-1.64}$ (0.08)***	
cDSTI cub1	**1.51** (0.04)***	
cDSTI cub2	**1.53** (0.12)***	
cDSTI cub3	**1.55** (0.03)***	
Has cDSTI*		$\mathbf{-1.51}$ (0.07)***
cDSTI* cub1		**1.40** (0.04)***
cDSTI* cub2		**1.18** (0.12)***
cDSTI* cub3		**1.46** (0.03)***
Origination time dummies	YES	YES
Bank dummies	YES	YES
Household economic activity	YES	YES
Observations	$4,842,974$	$4,842,974$
AUROC	0.9125	0.9121

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Coefficients in bold have p-values lower than 10^{-20}.

Terms cDSTI$^{(*)}$ cub1-3 refer to cubic spline polynomials, as in Mihai et al. (2018).

Figure 18: Personalised calibration of $\overline{\text{LTV}}_h^2$ – alternative objective function

(a) one-year horizon



(b) lifetime horizon

	Calibrated $\overline{\text{LTV}}^2$ limit: means and 90% confidence intervals							
	(a) one-year horizon				(b) lifetime horizon			
House price drop	**−15%**	**−20%**	**−25%**	**−30%**	**−15%**	**−20%**	**−25%**	**−30%**
$\text{cLTV}^1 > 70$	83 [82, 84]	81 [79, 82]	79 [76, 81]	77 [73, 80]	84 [83, 84]	82 [81, 83]	81 [79, 82]	80 [77, 82]
$\text{cLTV}^1 \in (0, 70]$	84 [83, 84]	82 [80, 83]	80 [78, 82]	79 [76, 81]	84 [83, 84]	83 [82, 84]	82 [80, 83]	81 [79, 82]
$\text{cLTV}^1 > 0$	83 [83, 84]	82 [80, 83]	80 [77, 82]	78 [75, 81]	84 [83, 84]	83 [81, 84]	82 [79, 83]	81 [78, 82]

Note: the chart maps a relationship between the personalised $\overline{\text{LTV}}_h^2$ limits and corresponding first loan LTV_h^1 ratios, using different calibration horizons and an alternative to equation (8) objective function: $\text{ECL}_h^2(\overline{\text{LTV}}_h^2, \text{LTV}_h^1) = \text{ECL}_h^H$. Vertical lines denote the averaged $\overline{\text{LTV}}^2$ limits with lightgrey rectangle areas being the 90% confidence intervals. The table below shows aggregate calibration results that are based on different horizons and house price drop (Δ) assumptions, by different subsets of households (by LTV_h^1).

B Model validation

To ensure the constructed model's accuracy, we measure its discriminatory power by performing the so-called Receiver Operating Characteristic (ROC) curve analysis, which is a standard validation procedure in classification exercises when dependent variable is dichotomous ('0' vs. '1'). The ROC curve shows how well the model discriminates one group ('1' cases) from the other ('0' cases), based on any threshold level – in our case, the level of loan's predicted one-year-ahead PD. For each possible threshold value γ, we compute the pair of accuracy measures:

$$\mathrm{TPR}_\gamma := \frac{\mathrm{TP}_\gamma}{\mathrm{P}} = \frac{\text{Number of correctly specified '1' cases}}{\text{Total number of '1' cases}} \qquad \text{(True positive rate);}$$

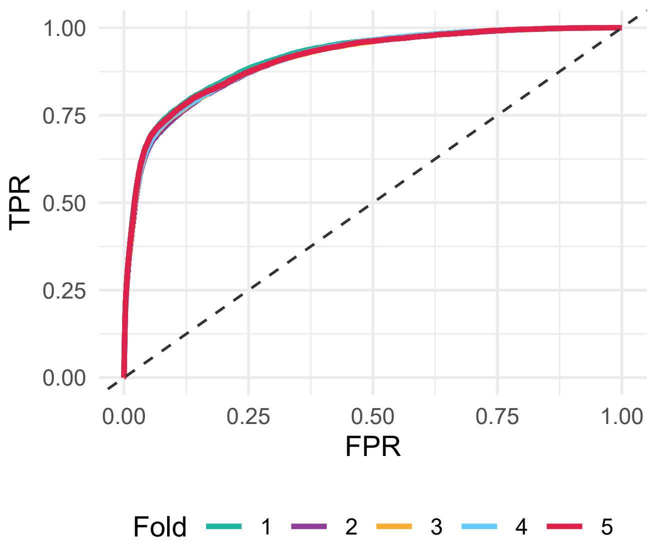
$$\mathrm{FPR}_\gamma := \frac{\mathrm{FP}_\gamma}{\mathrm{N}} = \frac{\text{Number of incorrectly specified '0' cases}}{\text{Total number of '0' cases}} \qquad \text{(False positive rate).}$$

The ROC curve is then constructed by plotting the FPR_γ on the x-axis against TPR_γ on the y-axis for each threshold γ (see Figure 19).

Since the ROC curve itself presents a set of possible combinations of TPR and FPR, a common and effective way to summarise the model's overall discriminatory power is by computing the area under the ROC curve (e.g., see Mandrekar, 2010). The measure itself is often called AUROC (*Area Under the ROC*) and attains possible values in the interval $[0, 1]$. The bigger the value, the more accurately the model discriminates between loans that do default and those that do not. Even though there are no strict guidelines as to at which AUROC level a classification model is signified as "good", it is usually deemed that 70% level is satisfactory.

To avoid overfitting, instead of computing AUROC values in-sample, we assess the model's discriminatory power by performing 5-fold cross-validation. The model is iteratively re-estimated on each of the 5 randomly selected training subsamples, and in each case the AUROC measure is obtained for the corresponding testing subsample. The resulting ROC curves and AUROC measures on each fold are presented in Figure 19. It is evident that the model discriminates non-performing loans very well, since the AUROC measure is more than 90%. Moreover, little variance in AUROC measures across different folds suggests of the stability of the PD model.

Figure 19: ROC curves for the baseline model



Fold:	1	2	3	4	5	Average
AUROC:	0.9088	0.9028	0.9038	0.9048	0.9058	0.9052

Notes: AUROC's correspond to measures of model's discriminatory power, using a 5-fold cross-validation procedure.

C Iso-impact curves

Assume that new limits on maturity and oDSTI$^{(*)}$, $\overline{M}$ and $\overline{\text{oDSTI}}^{(*)}$ respectively, are imposed. Since we are only considering policy tightening options, let $\overline{M} \leq 30$, $\overline{\text{oDSTI}} \leq 40$ and $\overline{\text{oDSTI}}^{*} \leq 50$. Naturally, given that new limits on borrower-based measures had been in place, some of the existing loan contracts would have been granted with altered conditions. In addition, some of the households might even have decided not to take mortgage loan at all. More specifically, consider an initial mortgage sample consisting of n individual loan contracts, each characterised by its initial amount D_k, actual oDSTI_k and oDSTI^*_k ratios and maturity at origination M_k, $k = 1, \ldots, n$. Denote the respective mortgage features after the policy intervention by $\widehat{D}_k$, $\widehat{\text{oDSTI}}_k$, $\widehat{\text{oDSTI}}^*_k$ and $\widehat{M}_k$. What follows, each BBM limits combination $\{\overline{\text{oDSTI}}, \overline{\text{oDSTI}}^*, \overline{M}\}$ reduce mortgage lending volume by $\Delta_D\%$, where:

$$\Delta_D = 1 - \frac{\sum_{k=1}^{n} \widehat{D}_k}{\sum_{k=1}^{n} D_k}.$$

Since the cases of tightening in oDSTI and oDSTI* are explored separately, iso-impact-on-credit curves (iso-impact curves for short) can thus be defined as follows:

- Tightening in oDSTI and maturity:

$$\text{Iso-impact}_{\text{oDSTI}}(\gamma) = \left\{ \{\overline{\text{oDSTI}}, \overline{\text{oDSTI}}^*, \overline{M}\} \mid \Delta_D = \gamma,\ \overline{\text{oDSTI}}^* = 50 \right\};$$

- Tightening in oDSTI* and maturity:

$$\text{Iso-impact}_{\text{oDSTI}^*}(\gamma) = \left\{ \{\overline{\text{oDSTI}}, \overline{\text{oDSTI}}^*, \overline{M}\} \mid \Delta_D = \gamma,\ \overline{\text{oDSTI}} = 40 \right\}.$$

Below we present a short algorithm which describes how individual loan characteristics $\widehat{D}_k$, $\widehat{\text{oDSTI}}_k$, $\widehat{\text{oDSTI}}^*_k$ are obtained:

- Say, the initial mortgage characteristics before policy intervention are D_k, $\text{oDSTI}_k \leq 40\%$, $\text{oDSTI}^*_k \leq 50\%$, $M_k \leq 30$ years;
- Besides the one-fits-all limits $\overline{\text{oDSTI}}$, $\overline{\text{oDSTI}}^*$ and $\overline{M}$ we assume that each household has its own individual preferences and risk tolerance. More specifically, each household will not take the mortgage if its initial size D_k would reduce more than 10% or its DSTI ratio would increase more than 10 p.p. due to the new regulatory framework. Effectively, this implies two new individual limits $\overline{D}_k = 0.9D_k$, $\overline{\text{oDSTI}}_k = \min\left\{\text{oDSTI}_k + 10\text{p.p.},\ \overline{\text{oDSTI}}\right\}$.
- If $M_k > \overline{M}$, we assume that mortgage was granted with limiting maturity $M_{0,k} = \overline{M}$. New oDSTI_k and oDSTI^*_k ratios, namely $\text{oDSTI}_{0,k}$ and $\text{oDSTI}^*_{0,k}$, are calculated under maturity horizon $M_{0,k}$, given that all other contract conditions remains the same.
  - (I) If $\text{oDSTI}_{0,k} \leq \overline{\text{oDSTI}}_k$ and $\text{oDSTI}^*_{0,k} \leq \overline{\text{oDSTI}}^*$, then the new mortgage is granted under a shorter maturity $M_{0,k}$, though its initial amount D_k is not affected.
  - (II) If $\text{oDSTI}_{0,k} > \overline{\text{oDSTI}}_k$ or $\text{oDSTI}^*_{0,k} > \overline{\text{oDSTI}}^*$, mortgage initial amount D_k is being reduced to the level $D_{0,k}$ until $\text{oDSTI}_{0,k}$ and $\text{oDSTI}^*_{0,k}$ ratios are within their limits. If $D_{0,k} \leq \overline{D}_k$, then the mortgage is not issued at all.
- If $M_k \leq \overline{M}$:
  - (I) If $\text{oDSTI}_k \leq \overline{\text{oDSTI}}_k$ and $\text{oDSTI}^*_k \leq \overline{\text{oDSTI}}^*$, then the new regulation will not affect this mortgage – it will be granted under the same conditions and same initial amount D_k;
  - (II) If $\text{oDSTI}_k > \overline{\text{oDSTI}}_k$ or $\text{oDSTI}^*_k > \overline{\text{oDSTI}}^*$, mortgage maturity M_k is being extended to $M_{0,k}$, until recalculated DSTI ratios, namely $\text{oDSTI}_{0,k}$ and $\text{oDSTI}^*_{0,k}$, are within the limits:
    - If $M_{0,k} \leq \overline{M}$, then the mortgage is granted under a shorter maturity $M_{0,k}$ and higher DSTI ratios, though its initial amount D_k is not affected.
    - If $M_{0,k} > \overline{M}$, then mortgage's initial amount D_k is being reduced to the level $D_{0,k}$ until oDSTI_k and oDSTI^*_k ratios are within their limits with limiting maturity horizon $\overline{M}$. If $D_{0,k} \leq \overline{D}_k$, then the mortgage is not issued at all.