

INTERNATIONAL MONETARY FUND

Micro-Assessment of Macroprudential Borrower-Based Measures in Lithuania

Mantas Dirma and Jaunius Karmelavičius

WP/23/227

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**2023
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WORKING PAPER

IMF Working Paper

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Micro-Assessment of Macroprudential Borrower-Based Measures in Lithuania*Prepared by Mantas Dirma[†] and Jaunius Karmelavičius[‡]

Authorized for distribution by David J. V. Hofman

October 2023

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ABSTRACT: Despite having introduced borrower-based measures (BBM), Lithuania's housing and mortgage markets were booming during the low-interest-rate period, casting doubt on the macroprudential toolkit's ability to contain excessive mortgage growth. This paper assesses the adequacy of BBMs' parametrization in Lithuania. We do so by building a novel lifetime expected credit loss framework that is founded on actual loan-level default and household income data. We show that the BBM package effectively contains mortgage credit risk and that housing loans are more resilient to stress than in the preregulatory era. Our BBM limit calibration exercise reveals that (1) in the low-rate environment, income-based measures could have been tighter; and (2) borrowers taking out secondary mortgages rightly are and should be required to pledge a higher down payment.

RECOMMENDED CITATION: Dirma, M., Karmelavičius, J. (2023). Micro-Assessment of Macroprudential Borrower-Based Measures in Lithuania. Working Papers WP/23/227, International Monetary Fund.

JEL Classification Numbers:	C25, E61, G18, G21, G51.
Keywords:	macroprudential policy; borrower-based measures; LTV; mortgage credit risk; lifetime expected loss; probability of default.
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*The views expressed are those of the authors and do not necessarily represent the official views of the International Monetary Fund, Bank of Lithuania or the Eurosystem.

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1 Introduction

In the aftermath of the Global Financial Crisis (GFC), waves of economies around the globe adopted macroprudential policy, including borrower-based measures (BBM) as well as capital buffer and liquidity requirements. Among those countries was Lithuania, which introduced its own BBM package in 2011 that was later followed by the imposition of macroprudential capital requirements. Much like in many other countries, the macroprudential toolkit was intended to address the harsh lessons of the 2000s’ financial cycle, which first accelerated the country’s financial inclusion and economic growth, and later swept its economy into a deep recession during the GFC.¹

Despite having macroprudential tools in place for more than a decade, today’s Europe is again finding its housing market overvalued, and with interest rates rising at an unprecedented pace, vulnerabilities are emerging (Valderrama and others, 2023). On the back of the then-low-interest-rate environment, Lithuania has been experiencing one of the highest house price and lending growth rates in the euro area that eventually led to its own mortgage market misalignments.² The situation brings on a *déjà vu*, questioning macroprudential policy’s ability to contain excessive credit and house price growth. Since the empirical literature strongly suggests that BBMs can be effective in smoothing credit cycles (e.g., see Biljanovska and others, 2023, and references therein), recent imbalances cast doubt on the appropriateness of the toolkit’s parametrization.

This is exactly the issue that this paper addresses. By using Lithuania’s rich household loan-level dataset spanning from 2004 to 2020 and containing information on family income and composition, we devise a framework that quantifies each individual mortgage loan’s credit risk. The micro-modeling setting enables us to assess how BBMs affect each mortgage’s lifetime performance, risk of default, and expected loss, allowing us to calibrate macroprudential BBM limits. On the other hand, our calibration exercise focuses on the micro-level and does not consider any feedback loops or externalities, which may be relevant from the macro perspective.

Using the proposed setup, we evaluate three key areas of Lithuania’s BBM framework: (1) efficacy of measures; (2) appropriateness of parametrization in the low-rate environment; and (3) regulation of secondary and subsequent mortgage loans.³ Our analysis is based on two years’ worth of behind-the-scenes policy work at the Bank of Lithuania and showcases how credit register loan-level information could be used for policy evaluation.

The paper documents seven findings that are relevant for policymakers across the globe, providing evidence that BBMs are effective in containing mortgage credit risk and boosting resilience.

¹For references on Lithuania’s experience and accumulation of imbalances preceding the 2009 crisis, see Ramanauskas (2005), Kulikauskas (2016), Karmelavičius and others (2022, 2023), and Cevik and Naik (2023). For coverage of the crisis period, refer to Kuodis and Ramanauskas (2009) and Ramanauskas (2011), and more recently to Baudino and others (2022), who analyze the events in the Baltic countries.

²Note that throughout this paper, we use the terms *mortgage*, *mortgage loan*, *housing loan*, and simply *loan* interchangeably and thereby refer to credit that is secured by residential real estate unless specified otherwise.

³A mortgage loan is “secondary” if during its inception, the household has at least one other active housing loan.

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 percent smaller than those experienced by Lithuania’s banking sector during the crisis.

Finding 2: Over the past decade mortgage quality increased and borrowers are now more resilient to adverse shocks compared with 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 debt-service-to-income (DSTI) cap, whereas the loan-to-value (LTV) measure is more suitable for controlling the loss given default.

Finding 4: The nonlinear relationship between the DSTI ratio and mortgage default probability suggests that in the low-rate environment, Lithuania’s DSTI limits were loose.

Finding 5: Were authorities aiming to reduce the pace of credit growth during the low-rate period, their first-best option would have been a joint reduction in both DSTI and maturity limits.

Finding 6: Secondary mortgages: (1) are more likely to default over their lifetime compared with an otherwise equivalent but single mortgage loan; and (2) impose a negative externality in terms of heightened default rate on the existing housing loan portfolio.

Finding 7: To compensate for the high probability of default of secondary mortgages, their regulatory LTV limit rightly is and should remain: (1) strictly lower than the headline LTV limit; and (2) differentiated by the current LTV of borrowers’ first mortgage.

Our work contributes to the body of writings on macroprudential policymaking in at least three major dimensions. First, within a sparse strand of literature, we develop an analytical framework that is based on actual loan-level default data and that models the credit risk of each individual mortgage. While there are many authors estimating the probability of default (PD) parameter, our PD model stands out from others with exceptionally high out-of-sample discriminatory power of around 90 percent, which can be traced to the inclusion of credit history variables. Additionally, we include the loss given default (LGD) parameter in our analysis to get a complete picture of credit risk by modeling lifetime expected credit losses (ECL) – in the spirit of IFRS 9 requirements for loss accounting.

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

As a third contribution, we dive into the investors’ segment and investigate the credit risk of secondary mortgage loans. While the literature on BBM calibration is scarce, loan-level-based

papers that study specific pockets of the market, like buy-to-let investors or secondary mortgages, are even rarer. Our analysis is among the few to calibrate an LTV limit for secondary mortgages, with the notable exception of Kelly and O’Toole (2018), who analyze multi-loan borrowers.

The paper is structured as follows. Section 2 presents some background information on the Lithuanian BBM setting and recent dynamics of the mortgage market. Section 3 develops a credit risk modeling framework, which is used for the assessment of BBMs 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 on BBMs in Lithuania, recent dynamics of the mortgage market, and discuss some BBM policy options.

2.1 Institutional Setup

In Lithuania, macroprudential policy is conducted solely by the central bank. Among Bank of Lithuania’s macroprudential policy tools are BBMs, which were adopted in 2011 through the enactment of Responsible Lending Regulations (*Atsakingojo skolinimo nuostatai*, or ASN).⁴ Although the framework applies to all credit extended to natural persons and secured by real estate, we focus only on residential housing loans, which comprise the majority of loans under the regulation.⁵

The BBMs that are within the scope of ASN limit borrowers’ mortgage credit uptake through a requirement of a down payment, a limit on loan maturity, and monthly installments. Table 1 summarizes ASN measures and their corresponding limits in place at the time of writing this paper. Specifically, the LTV requirement puts an 85 percent limit on the loan amount compared with the value of pledged real estate collateral. The latter limit implies a 15 percent minimum down payment requirement for a leveraged house purchase.⁶

As of February 1, 2022, the LTV limit was restricted to 70 percent for second and subsequent (LTV²) mortgage loans, with an exemption for borrowers whose first mortgage current LTV is lower than 50 percent at the time the secondary mortgage is extended.⁷ The more stringent

⁴Links 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.

⁵The regulation applies to all credit providers that are profit-seeking legal persons, including domestic banks and foreign branches, credit unions, peer-to-peer lending platform operators, and other non-bank financial intermediaries that operate in Lithuanian jurisdiction. In principle, the wide scope of application of the ASN requirements minimizes the possibility of circumvention, i.e., leakage effects.

⁶Importantly, the ASN framework disallows the use of borrowed funds for a down payment, implying that the borrowing party must 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.

⁷See announcement news.

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

Note: LTV² denotes the LTV limit for secondary mortgages, effective as of February 1, 2022. The 70 percent limit for LTV² is applied only for borrowers whose first mortgage's current LTV is above 50 percent at the inception of the secondary mortgage. Credit institutions may use an exemption and apply a DSTI limit of 60 percent for creditworthy customers; however, the amount of loans issued with such exemptions cannot exceed 5 percent of the institution's annual mortgage flow. DSTI* denotes the stressed DSTI limit, which cannot be exceeded after applying a 5 percent interest rate sensitivity test.

LTV² \leq 70% requirement was imposed to limit leveraged investments that are putting additional strain on the housing market, and to equalize 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 LTV² limit is covered in Section 5.

While the cap on the LTV can be viewed as a solvency requirement that is related to the borrower's equity or own funds, the DSTI limit is more of a liquidity measure. Essentially, the DSTI requirement imposes a 40 percent limit on average monthly loan payments, i.e., installments and interest payments, as a share of the borrower's monthly disposable income. To safeguard borrowers, including leveraged buy-to-let investors, against taking up excessive debt during the low-rate period, and to increase their resilience to possible future interest rate shocks, the Bank of Lithuania imposed an additional stressed DSTI* \leq 50% limit, whereby DSTI* is computed with stressed interest rate to 5 percent. Given the fact that almost all mortgage loans in Lithuania are granted with variable rates, such measure mitigates the impact of interest rate rises, especially for loans that were initiated in the low-rate environment.

The 30-year loan maturity limit that was introduced in 2015 serves two functions.⁸ First, when combined with the DSTI requirement, they limit borrowers' indebtedness over income, i.e., debt-to-income (DTI). Second, a ceiling on the duration of a credit agreement enhances consumer protection by requiring at least some amount of amortization, and disallowing perpetual interest payments, thus lowering the cumulative amount of interest paid by the borrower.

2.2 Effects of Borrower-Based Measures

The international literature finds BBMs to be primarily operating through two channels. First, the tools enhance the resilience of households and creditors to shocks (e.g., Gross and Población, 2017; Ampudia and others, 2021; Giannoulakis and others, 2023). Second, appropriately parametrized BBMs can smooth credit demand over the financial cycle, potentially reducing the probability of high asset price growth and the accumulation of imbalances (e.g., Cerutti and others, 2017; Alam and others, 2019; Poghosyan, 2019; Araujo and others, 2020).

⁸See announcement news.

The effectiveness of Lithuania’s ASN framework 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 worked countercyclically. The author empirically estimates that had the LTV requirement not been introduced in 2011, the household loan portfolio would have grown, on average, 1.5 percentage point (p.p.) faster (over 2012-14), leading to a 0.5 p.p. higher average house price growth. Further, implementing the LTV limit in the 2000s would have substantially helped temper the credit and housing boom.

In addition, Rutkauskas and others (2015, p. 72) stress-tested Lithuanian household credit portfolio using loan-level data and found the portfolio to be resilient to adverse scenarios. The authors concluded that the ASN framework, in particular DSTI and LTV requirements, increased the shock absorption capacity of household loans. Complementing this, Matkėnaitė and others (2016) show that if the LTV requirement had been present before the GFC, it would have significantly boosted the banking sector’s resilience to a house price correction – mortgage credit losses would have been 83 percent smaller than those in 2009.

Using a dynamic stochastic general equilibrium (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 may increase resilience by reducing the mortgage delinquency rate. Specifically, a 1 p.p. tightening of the LTV limit decreases the mortgage portfolio by -0.5 percent and house prices by -0.15 percent, lowers mortgage default rate by -1.75 p.p., with an impact on GDP being around -0.1 percent.

Besides the resilience and countercyclicality effects of BBMs, one has to acknowledge that there may be unintended social consequences of such regulation. Matkėnaitė and others (2016) argue that LTV regulation restricts access to housing and reduces home ownership. For example, financially constrained people are forced to rent housing for prolonged periods, 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 bulk, thus raising both house prices and rental rates, and eventually wealth inequality.⁹ The long-term side effects of BBM regulation in Lithuania remain to be seen; however, we can already observe that over the past decade since the inception of ASN, rental prices have accelerated and grown, on average, 1 p.p. higher than house prices on an annual basis.

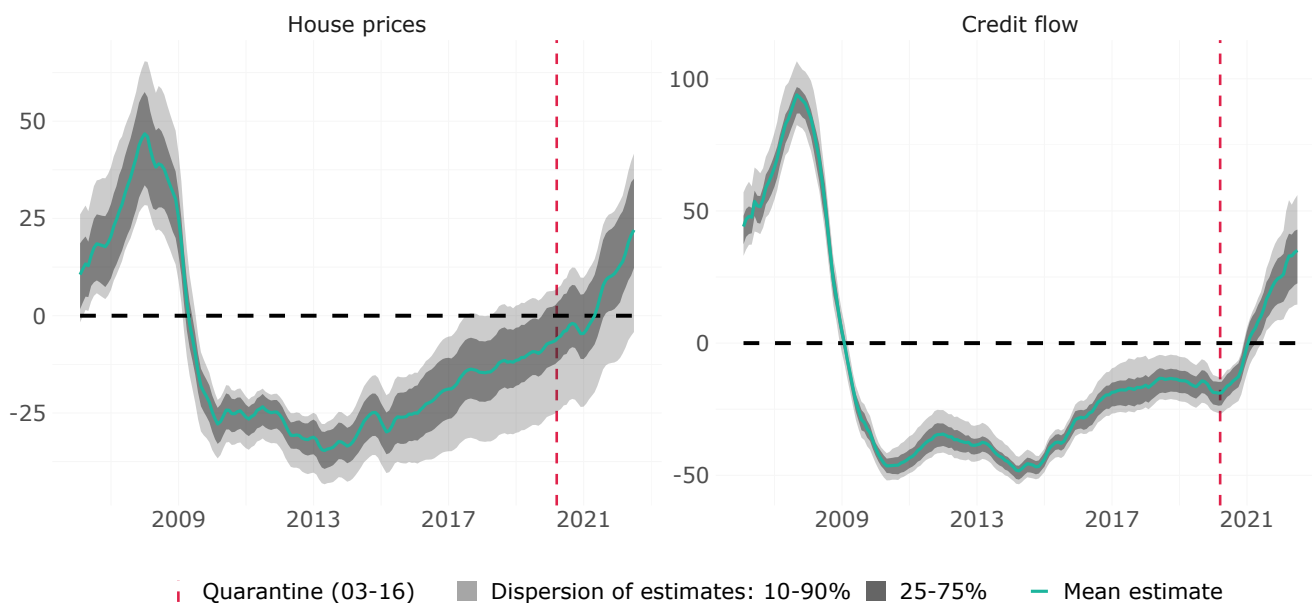
2.3 Mortgage Market Dynamics

Although the ASN framework had been present for more than a decade, Lithuania’s housing market has been one of the most dynamic in the euro area. For the past couple of years, house prices and mortgage portfolio have been growing at a double-digit annual pace, with year-on-year

⁹For an international perspective on macroprudential policy’s distributional effects, see Acharya and others (2022), Tzur-Ilan (2023), Malovaná and others (2023), and Teixeira (2023).

growth rates peaking at 26.8 percent and 12.3 percent, respectively. The COVID-19 pandemic did little to slow 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 and others (2022). The series are percent deviations from fundamental values

During a prolonged period of high growth, imbalances accumulated and gaps opened, as indicated by different statistical models, including the two-market disequilibrium approach of Karmelavičius and others (2022) depicted in Figure 1. Recent measurements of misalignments suggest that by the end of 2022, home prices were up to 20 percent above their fundamentals and that there was a mortgage credit overflow of around 15 percent.¹⁰ Although newer data suggest a slowdown in credit and house price growth due to sharply raised interest rates, putting downward pressure on positive gaps, the authorities should monitor the mortgage market carefully and be vigilant about systemic vulnerabilities.¹¹

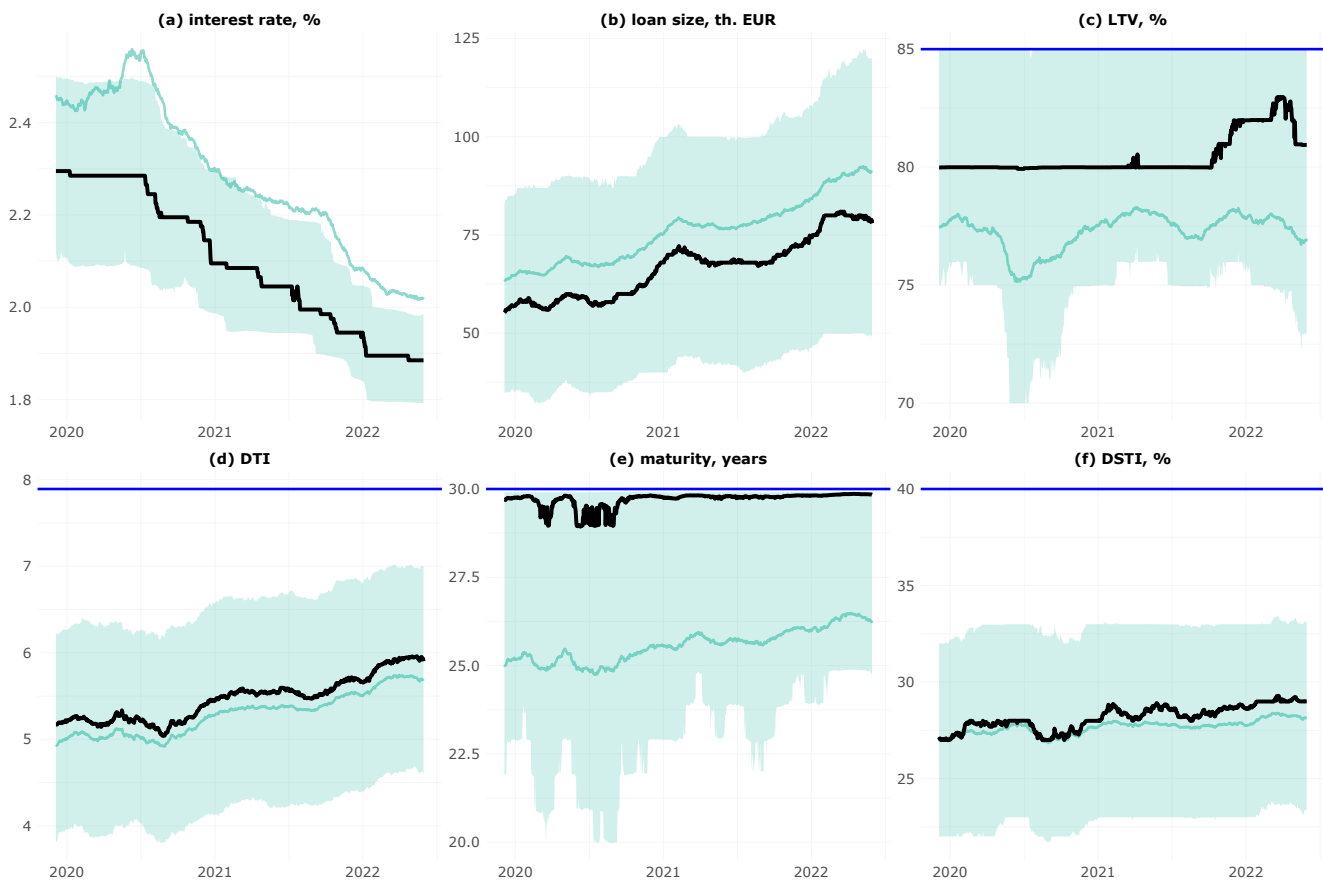
The recent opening of house price and credit gaps can be understood as both the cause and effect of deteriorating lending standards. We inspect by examining aggregate trends of loan-level characteristics, such as interest rates, loan size, LTV, and other metrics (Figure 2). As depicted,

¹⁰Although Lithuania stood out among other European countries in terms of high real house price growth, a recent paper by Valderrama and others (2023, Figure 2) finds Lithuania’s home price overvaluation to be modest, as indicated by the price-to-rent ratio. While simple price-to-income and price-to-rent ratios can be useful, they omit important macrofinancial variables, such as interest rates, population growth, output gaps. Karmelavičius and others (2022) find that econometric model-based indicators suggest of a moderate level of misalignments in Lithuania, although comparatively lower than in some other European countries, and lower than those observed in the 2000s.

¹¹The 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 and the overflow gap depicted on the right side of Figure 1 does not close, it can invoke a positive mortgage credit-to-GDP gap.

from 2020 through mid-2022, just before the shift in monetary policy stance, there was a deep fall in mortgage rates for new lending. Not only did the median rate drop from 2.3 percent to 1.9 percent, but the rates became more compressed around the median. This process aligned with the more active participation of some banks in the credit market, suggesting higher competitive pressures.

Figure 2: Rolling Characteristics of New Housing Loans



Notes: Two-month rolling means (green line), medians (black line), and IQRs (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 the period when the Euribor was still negative and the Euribor floor was applied. Data is sourced from the new PRDB database – credit register.

In response to increasing home prices, changing housing preferences, and decreasing interest rates, the average loan size rose from 60 to 90 thousand EUR – a 40 percent increment over two years. As household disposable income growth lagged behind increasing home values, it became increasingly difficult to accumulate a down payment, thus household indebtedness slightly increased in terms of median LTV and DTI ratios. Although the average housing loan size was rising faster than household income, DSTI ratios remained remarkably stable – an effect of lower interest rate margins and somewhat longer maturities. Nonetheless, by now the burden of debt service payments for variable-rate loans, which comprise more than 90 percent of the market, has increased significantly along with sharply elevated policy 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 the share of secondary mortgages in new lending flow increased from 9.9 percent to 12.9 percent during 2019-21. At the regional level, this increase is common across Lithuania, with the biggest gains in the coastal region of Klaipėda, Palanga and Neringa – a resort area. Historically, the share of secondary mortgages has been 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.¹²

Customers taking out a secondary housing loan are most likely buying a house that will not be their primary residence and will be used either for own leisure purposes, e.g., in coastal resort areas, or for investment as a rental property.¹³ Considering this, it is likely that the credit risk of a household with a secondary loan is greater than that of a household with a single mortgage. There are two primary reasons for this.¹⁴

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 in panel (c) of Figure 3, where one can see that DSTI distribution of secondary loans is heavily shifted rightward. Households that have more than one mortgage are more susceptible to changes in interest rates and loss of income, whether rental, labor, 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. Figure 3(c) shows that the LTV distribution of secondary mortgages is concentrated around 80 percent – more than half of loans have LTVs that are between 80 and 85 percent – deemed relatively high for secondary loans.¹⁵ Also, the data do not show any negative relationship between

¹²Nonetheless, secondary mortgages may produce economic value for both individual borrowers and for society as a whole. The latter stems from the fact that secondary mortgages are often used for financing betterment, e.g., refurbishment, of existing low-quality housing units. Also, secondary mortgages may create value for lessees or tenants, increasing the supply and quality of the rental market. Notwithstanding, one has to bear in mind that secondary mortgages are merely a means of financing an end – investment into housing that can otherwise be acquired with own funds.

¹³In some cases, customers switch their primary residence to the second house and rent out their first house. In other instances, parents may take out secondary mortgages and buy apartments in urban areas, e.g., capital city Vilnius, for use by their children.

¹⁴Kukk (2021) notes that there are two reasons why people default, namely, the “equity” and the “ability to pay” theories. The equity theory explains strategic default, which is mostly related to the 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, the equity theory is less relevant for European countries, since most of them have full recourse systems.

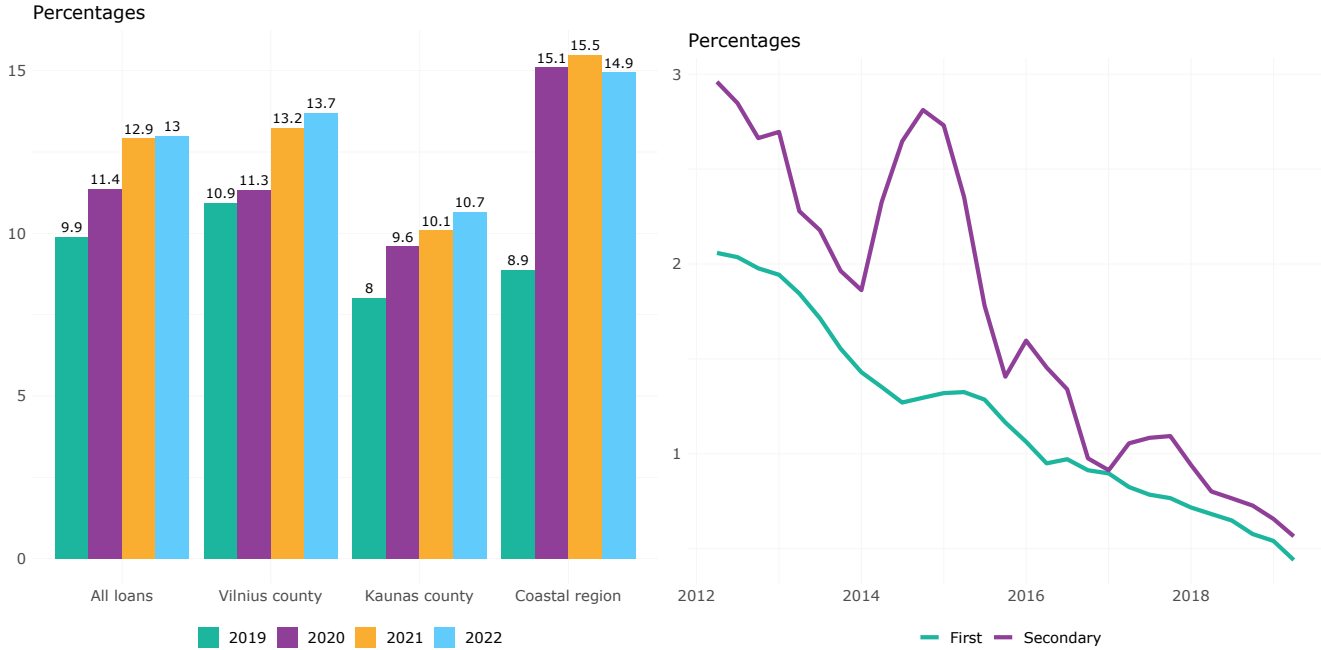
¹⁵Under the regulation that was valid until February 1, 2022, strictly lower than 85 percent LTV limit for secondary mortgage loans was imposed.

the LTVs of secondary mortgages and corresponding first mortgage LTVs.

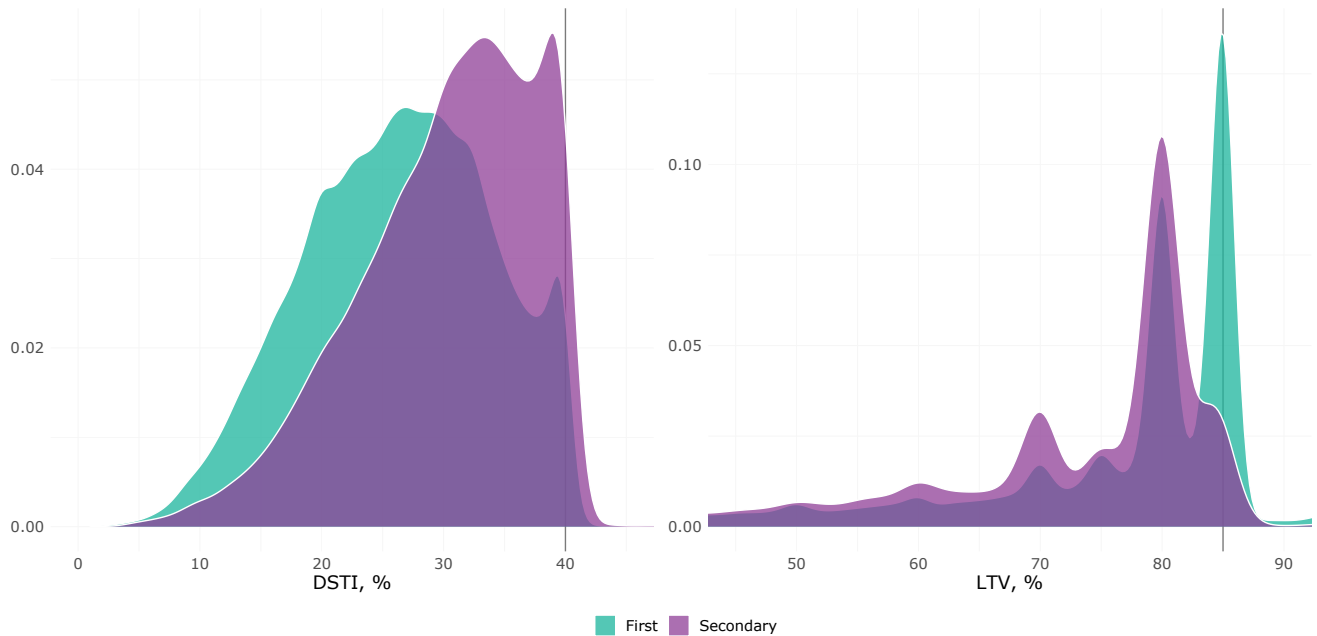
Figure 3: Properties of Secondary Mortgages

(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 nonperforming (over one-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.

Although natural person bankruptcy protection in Lithuania and the EU is frail, i.e., partial or

full recourse systems, once housing value drops and a secondary mortgage becomes an underwater loan, the debtor will be less likely to hold onto that nonprimary residence and default, implying a higher PD parameter. Further, in a full or partial recourse system, 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 dimension of risk via elevated LGD parameter.

The idea that secondary mortgages do default more often is supported by our data, as shown by Lithuania's historical delinquency rate series in Figure 3(b). Throughout 2012-20, while the first mortgage average default rate was around 1 percent, the secondary mortgage default rate was over 1.5 percent – a 50 percent higher chance of nonperformance. 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 the 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. Further, secondary mortgages are riskier, because they are not taken out by first-time buyers, who are known to be low-risk borrowers, as found by Kelly and others (2015), Mihai and others (2018), and Nier and others (2019), among others. Lastly, Baptista and others (2016), using an agent-based modeling setting, show that buy-to-let investors “may amplify house price cycles and increase house price volatility.” Building on this evidence, Section 5 illustrates that based on 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.

Finally, moving from a micro- to macroprudential argument, if secondary mortgages are prevalent, they add fuel to the housing market, contributing to existing home prices 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 risky 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 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 considering arguments like the one above, the Bank of Lithuania strengthened the regulation of secondary mortgages by imposing a 70 percent LTV² limit, which came into effect on February 1, 2022 (see Table 1). Section 5 explains the secondary mortgage LTV² limit assessment made before the policy conclusion was reached.

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					

Note: This table was compiled and provided by Mrs. Milda Stankuvienė, a Senior Economist of Bank of Lithuania, on June 1, 2022. Note that BBM frameworks are not harmonized across countries, with various peculiar qualitative features and exemptions; therefore, one must look at this table as only one of many possible representations.

The LTV limit is the maximum limit that is effective in each jurisdiction. For example, if a country has an LTV limit of 95 percent for first-time buyers and 80 percent for others, then 95 percent = $\max\{80\%, 95\%$ is considered to be the prevailing one. The effective DTI limit is calculated by taking the DSTI, stressed DSTI and maturity limits into account, and assuming a 2 percent 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 percent DSTI limit is assumed, as in Lithuania. *** assuming that Loan-to-Income (LTI) ratio is equal to DTI, i.e., there is only a single loan per borrower.

2.4 Tightening Options

Although recent interest rate hikes are already deflating mortgage market pressure, exuberance and associated misalignments that existed during the low-rate episode suggest that Lithuania's macroprudential stance had been loose. While it is agreeable that BBMs are primarily aimed to boost resilience of lenders and debtors, it is also desirable for the toolkit to work countercyclically

and dampen formation of imbalances. From the latter perspective, an opening of credit gaps, like those depicted in Figure 1, signals that the ASN framework had not been binding enough.

On the other hand, if compared with BBMs in other European countries (Table 2), Lithuania's regulation is quite tight. For example, the LTV limit of 85 percent ranks as the 2nd strictest, with many states having an LTV that is looser – 90 percent, 95 percent, or even 100 percent. As income-based regulation is more diverse across different countries, we compare the effective DTI cap that is calculated using a DSTI limit and maturity cap. In terms of the effective DTI requirement, Lithuania is once again among the jurisdictions with more stringent limits. Comparing with the other two Baltic countries with a similar risk profile, Latvia and Estonia, Lithuania has the most restrictive LTV, while its effective DTI is the least stringent of the three.

It is noteworthy that when conducting a comparative analysis as such, one must consider that BBM frameworks across Europe are not necessarily optimal. In some cases, BBM limits are relatively loose, which may have been influenced by low affordability of housing. Also, this country comparison exercise is only partial, as it does not consider other macroprudential tools. For example, some countries may compensate relatively loose BBM stance with higher macroprudential capital requirements, e.g., in the form of systemic risk buffers for exposures to residential real estate. In fact, at the time of writing this paper, such regulation is applied in Belgium, Germany, Liechtenstein, Slovenia, and also in Lithuania.

2.4.1 Active Changes in Policy

While specific BBM limits of the ASN framework may be seen as time-invariant parameters, in principle, they could be used countercyclically to tackle misalignments – positive or 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 and others (2013), Mendicino and Punzi (2014), Rubio and Carrasco-Gallego (2014), and Bruneau and others (2018).¹⁶ More recently, Gatt (2021) and Ferrero and others (2022) look at LTV rules in settings with occasionally binding constraints, and find that LTV caps should be changed countercyclically. Interestingly, Gatt (2021) shows that a time-varying LTV rule should react asymmetrically, i.e., tightening should occur more aggressively during credit booms, creating ample space for loosening during busts.¹⁷

¹⁶Welfare 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 macroeconomic and financial stability gains from having a policy rule that entails a time-varying LTV ratio (Lambertini and others, 2013; Rubio and Carrasco-Gallego, 2014; Rubio and Comunale, 2016).

¹⁷Rubio 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 and others (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.

While DSGE-based analyses overwhelmingly show that time-varying LTV rules can improve welfare, there are serious practical considerations for such policy setup. First, actual loan contracts' LTV ratio 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 BBMs is highly asymmetric across different stages of the credit cycle (e.g., see Richter and others, 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.¹⁸

Second, conducting a policy of actively changing BBM parameters may be challenging from the policymaker's perspective. Implementation of such framework should be based on the identification of the financial cycle phase, which is a complex 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 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, especially in the early stage of macroprudential framework.

Third, a single change in BBMs is highly distortionary for credit, housing, and rental markets, let alone frequent changes that add a layer of uncertainty for market participants. While alterations in regulation certainly affect creditors – as they must comply with new requirements and alter their own risk-assessment frameworks; frequent changes can be particularly worrisome for home-buying households, especially when they are financially constrained. From the customer's perspective, taking out a housing loan is a significant long-term decision that requires financial planning and investment in the down payment. Any unexpected tightening of BBMs, like the LTV requirement, will markedly alter purchasing plans or arrangements; thus, the household will likely have to choose a home of lesser quality, delay purchase, or incur a financial loss.¹⁹ Conversely, an early announcement of a future increase in regulatory requirements would incentivize households to rush to 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 and generate public mistrust toward the regulator, leading to likely reputational damage.

¹⁸Figure 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 GFC (see Figure 7 of Matkėnaitė and others, 2016). For a comparison of the two periods, see Appendix D of Reichenbachas (2020).

¹⁹Households 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 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.

Finally, since BBMs affect housing affordability, the regulation is socially sensitive; thus, there are substantial risks for the toolkit, or the process of changing it, to become politicized. Frequent changes in BBMs may draw intrusive attention from politicians or special interest groups or lobbyists, who could try to influence the decision-making process, ultimately jeopardizing the independence of the policymaking institution.

2.4.2 A One-off Tightening

Based on the outlined arguments, it is clear that the number of operational issues caused by frequent changes in BBM limits overwhelms the DSGE-based evidence. Perhaps that is why active changes in BBM regulation, whether discretionary or rules-based, are rarely practiced. As Matkénaitė and others (2016) argue, it may be good to have a longstanding BBM framework with fixed parameters, setting a standard for all market participants, promoting a sense of certainty. After all, LTV and DSTI limits improve resilience and act countercyclically, even if they are unchanged throughout the cycle.

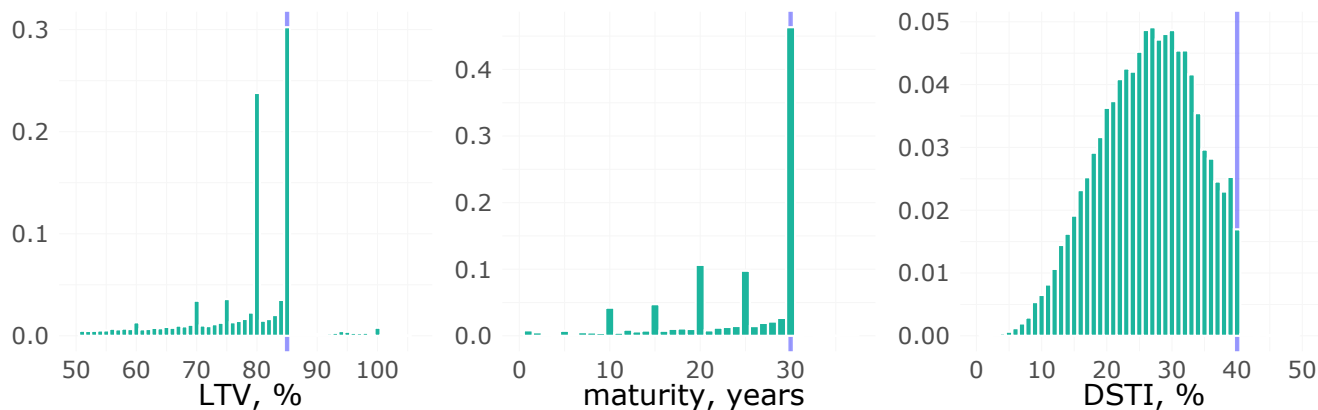
However, the latter logic does not rule out discretionary changes in BBMs, when they are occasional recalibrations of the toolkit. On the contrary, if there is strong evidence that the macroprudential stance is inappropriate, e.g., loose, the designated authority may tighten the regulation, as long as the alterations are not too frequent. This approach is supported by Brandao-Marques and others (2020), who empirically find that tightening BBMs can be particularly beneficial if financial vulnerabilities are on the rise. Based on this argument, the heat that was observed during the low-rate period may have been contained by imposing stricter ASN limits. In that case, policymakers would be creating additional space for policy relaxation if steeply rising interest rates depress lending and overburden the general economy.

Before exploring the options for tightening, first, we investigate how binding the ASN parameters are in Lithuania. Figure 4 shows that throughout 2019-22, LTV and maturity limits were significantly more binding than the DSTI cap. Around 37 percent of newly issued loans had a limiting LTV of 85 percent and 48 percent had an LTV that was just below the cap, i.e., $LTV \in (80\%, 85\%]$. If at the time the regulator decided to tighten the LTV limit to 80 percent, it would impact roughly half of the lending flow. Turning to the maturity limit, around 31 percent of mortgages had their maturities designated at the 30-year limit, and 64 percent of new loans would have been affected by tightening of the mortgage duration cap to 25 years. The corresponding figure for the DSTI cap of 40 percent would be only 1 percent, and tightening the DSTI cap to 35 percent would have affected around 16 percent of the mortgage flow.

As BBM parameters are usually set in five-unit intervals (see Table 2), the tightening of LTV by 5 p.p. would have been the most impactful, compared with the effect of setting the DSTI limit to 35 percent. This is exactly the reason we argue that from a policymaker's perspective, tightening the DSTI limit by 5 p.p. could have been a better option: it is less impactful, but also

less distortionary. Tightening the LTV limit would significantly affect around half of mortgage issuance, mostly to first-time buyers, many of whom are financially constrained young families, independently of their risk profile. In a vast number of cases, credit institutions grant mortgages with a maximum LTV of 85 percent, or close to it, only if housing collateral is good quality and the debtor is low risk. Tightening LTV to 80 percent would disproportionately affect mortgage contracts that are low risk, i.e., trustworthy borrowers with high-quality collateral.

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%

Note: 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.

Conversely, if the DSTI option had been chosen, it would have affected around 15 percent of borrowers – roughly the size of mortgage overflow – whose DSTI is on the righthand side of the distribution (see Figure 4b). Stricter regulation of DSTI^(*) – headline DSTI or the stressed DSTI^{*} – would be more targeted to containment of risk, since the ratios are strongly related to the customer’s PD, as shown by multiple authors, including Mihai and others (2018), Galán and Lamas (2019), and Nier and others (2019). Using a comprehensive framework, Gross and Población (2017) find that “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 BBMs – the ASN framework – and overviewed recent mortgage market dynamics that took place before interest rates were hiked. Based on this background discussion, the next section develops a micro credit risk model, then uses it for an in-depth assessment of the DSTI^(*) cap from a quantitative perspective, and lastly showcases the calibration exercise of LTV limit for secondary mortgages.

3 Modeling Mortgage Risk

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

Brief Overview of Methods

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

The second approach deals with BBM analysis in an agent-based simulation setting that accounts for heterogeneity across multiple borrowers and loan contracts by typically exploiting survey data. Macroprudential policy literature that uses agent-based models is relatively new and includes papers by Baptista and others (2016), Cokayne (2019), Laliotis and others (2020), Catapano and others (2021), or Tarne and others (2022). This strand of literature typically finds that BBMs reduce mortgage risk and slow the credit and housing cycle. In addition, the strand finds the impact of instruments highly nonlinear, dependent on the distribution of households and loan contracts. The latter finding confirms the importance of granular data for addressing household heterogeneity when calibrating BBMs.

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 for the analysis of how aggregate shocks are propagated to household default. The literature, which is based on the model and includes works of Jurča and others (2020), Ampudia and others (2021), and Neugebauer and others (2021), finds that BBMs 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 methods described rely on survey data and simulated default, the fourth approach is based on modeling actual loan-level defaults. 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 factual default and loan data. However, since micro level data availability and

often quality are major obstacles for researchers, the use of such method is not as prevalent as might be expected. Authors that use this approach include Kelly and others (2015), Kelly and O’Toole (2018), Mihai and others (2018), Galán and Lamas (2019), Nier and others (2019), de Haan and Mastrogiacomo (2020), Andries and others (2021), and Kukk (2021). They typically find that BBMs, 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 evaluating the PD parameter, overlooking the LGD, and often ignore the time dimension of credit risk, solely focusing on one-year-ahead assessments.

Our Modeling Approach

This section and the rest of the paper are based on the aforementioned 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 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 modeling setting and evaluate credit risk comprehensively by including both PD and LGD parameters in the analysis for computation of ECL.

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

As mortgages are long-term contracts, usually up to 30 years (see Figure 4), we generalize the one-year-ahead loss framework to compute lifetime ECL. To this end, we compute unconditional t -period PD and LGD parameters that are based on constructed amortization schedules for each loan. This section first describes our dataset, then outlines the estimation results of the PD model, and finally turns to the lifetime ECL framework.

3.1 Data

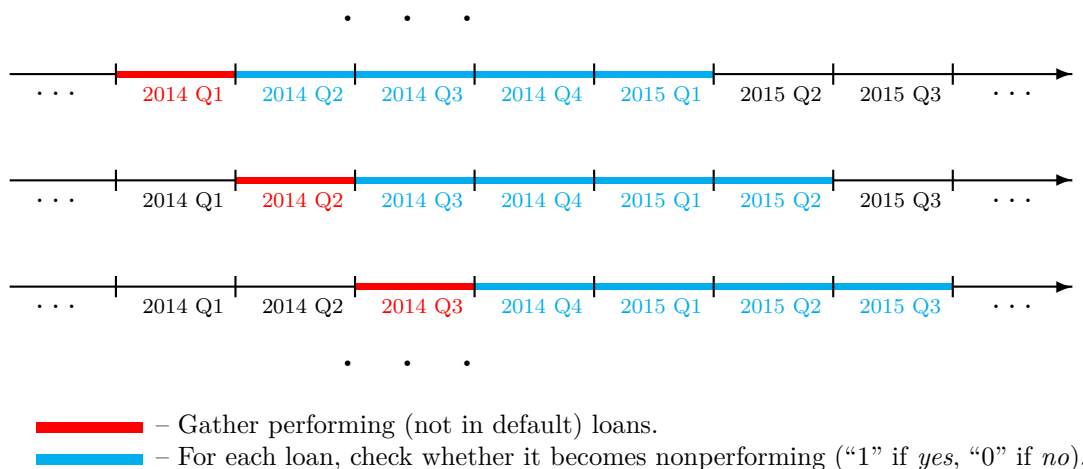
The main data source we use to model mortgage credit risk is Lithuania’s household credit register, which contains loan-level information about resident households’ credit agreements.²⁰ The granularity of the dataset allows us to observe main household characteristics like family composition, income, economic activity type of each household member, as well as details about their credit obligations – amounts outstanding, interest rates, installments, 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

²⁰The dataset is NŪFSIS (*Lith.* Namų ūkių finansinės stebėsenos informacinė sistema; household finance monitoring system), a system that joins the credit register with the household register and social insurance (SoDra) database. The same NŪFSIS database was used by Rutkauskas and others (2015). A recent report on household finance, which uses data from the database, is available here ([link](#)).

days, or written off. The data are observed at quarterly frequency and span from 2004 to 2020, covering the boom-bust cycle surrounding the GFC, 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 must 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 variable for modeling one-year-ahead PDs is constructed using an iterative procedure, which is depicted in Figure 5. For every loan-quarter combination, we: (1) assign “1” if the loan is performing at that quarter but defaults within the next year; (2) assign “0” if the loan is performing during the given quarter and performing within the next year; or (3) remove the observation altogether if the loan is not performing at that 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 the 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 installments 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:

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

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 after-tax or net income. The numerator of DTI – household debt – is taken as a sum of outstanding balances of a household’s all credit agreements.²¹ 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.²²

As we are interested in measuring mortgage-level credit risk, we take additional steps for cases when a single loan has multiple households-debtors: (1) loan payback expenses, outstanding balance and monthly income are aggregated across all households; and (2) 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 dimensions, allowing for the observation of each mortgage’s evolution 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 period 2004-20.

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 one-year-ahead PDs and later expand the time horizon. For every mortgage at a given quarter, we estimate the probability of it becoming nonperforming at least once within the next year using the following logistic regression model specification:

$$\text{logit}(\text{PD}_{k,t}) := \ln \left(\frac{\text{PD}_{k,t}}{1 - \text{PD}_{k,t}} \right) = \beta_0 + \beta_1^\top \mathbf{x}_{k,t} + \beta_2^\top \mathbf{z}_{k,t} + \varphi(\text{oBBM}_k), \quad (1)$$

where $\text{PD}_{k,t}$ is the one-year-ahead PD for housing loan k at quarter t , since origination is measured in years; $\mathbf{x}_{k,t}$ 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 .²³

Since our analysis is focused on the evaluation of BBMs, we include the $\text{D(S)TI}^{(*)}$ 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·)

²¹To deal with outliers for the majority of continuous variables, we winsorize them by setting extreme values to some specific predefined quantile or threshold. For instance, we cap DSTI and LTV ratios at 300 percent and DTI at 67.

²²Since our NÜFSIS dataset does not contain accurate location of each collateral unit, we used the national house price index as a proxy. Overall, this should not be a binding assumption, since home price indices are well correlated across different cities and regions, as depicted in Figures 1 and 2 of Cevik and Naik (2023).

²³One-year-ahead PD at l -th quarter since the origination has index $t = l/4$.

is that BBMs 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 the performance of a loan throughout its lifetime. Moreover, similar to Kelly and others (2015), Kelly and O’Toole (2018), and Mihai and others (2018), we use the restricted cubic splines transformation $\varphi(\cdot)$ for income-based debt ratios (oD(S)TI^(*) and oDTI).²⁴ This nonparametric technique captures more intricate nonlinear effects of income-based variables on 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 percent, as measured by the AUROC statistic, calculated using the five-fold cross-validation procedure (see Appendix B for details). In comparison, Kelly and O’Toole (2018) are able to fit a model with the AUROC up to 73 percent, and Mihai and others (2018) up to 80 percent. The main difference in discriminatory power compared with the two papers can be attributed to including in our model credit history variables, without which the AUROC would be closer to that of Mihai and others (2018).

Now, we briefly discuss the baseline model parameter estimates, which can be divided into three groups: (1) borrower and loan features; (2) macroeconomic variables; and (3) BBM-related variables (Table 5, Model 1 column).

The first block includes various borrower and loan features, such as maturity, interest rate, income, credit history, etc. We can see that the residual maturity of a loan is significant and positively related to one-year-ahead PD, meaning that customer default is more likely at earlier stages of a housing loan’s lifespan.²⁵ The results also suggest that higher interest rates may significantly increase the risk of default throughout the life cycle of a loan.²⁶ Importantly (thus covered in depth in Section 5), the fact that a customer has more than one housing loan may statistically significantly increase the likelihood of mortgage default. Further, model estimates suggest that borrowers who 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 are significant for the model’s discriminatory

²⁴The 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.

²⁵This 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 about keeping that loan active. Also, at least for annuity schedules, installments are more sensitive to changes in interest rates at the early stages of a loan’s lifetime.

²⁶The 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 result in higher interest rates as a compensation for higher credit risk.

power.²⁷

Regarding macroeconomic variables, we can see that customer default frequency is countercyclical, i.e., the PD is lower when the economy is growing and the unemployment rate and inflation are low, albeit the magnitude of their impact is rather limited. Interestingly, the unemployment rate is statistically significant at even the most conservative levels, suggesting that households' ability to service debt is dependent on labor 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 those issued afterward.

Turning to oLTV and oD(S)TI^(*) variables, which are directly related to BBM limits, they are significant for mortgage default. Section 4 covers these results extensively, but we can already see that a 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 and others (2020), or Ampudia and others (2021), the magnitude of the impact of oDSTI measures on PD is higher compared with that of oLTV. Also, the cubic spline terms of oD(S)TI^(*) are statistically significant, suggesting 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 after origination. Therefore, a calibration of BBM instruments should consider how BBM-related variables at origination affect successive loan evolution, i.e., the period from initial recognition to final maturity. Also, the evaluation of the PD parameter cannot be the sole focus, as credit risk is also related to the LGD parameter. With these arguments in mind, we transit our BBM-assessment framework from one-year-ahead PDs to lifetime ECLs.²⁸ The concept of credit risk assessment over the life cycle of a loan is crucial, because we seek to evaluate the potential interactions of loan maturity with other BBMs, like the DSTI cap.

²⁷If a household had 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 nonperforming over a one year horizon.

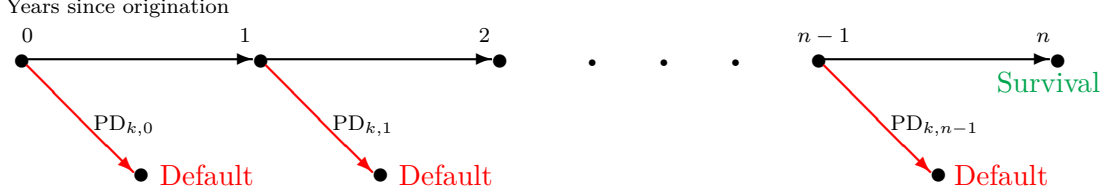
²⁸Since the introduction of the new IFRS 9 accounting standards, survival analysis models became more prevalent in the context of credit risk assessment. According to the IFRS 9 regulations, loans whose credit risk increased significantly since their initial recognition, or which became impaired, are subject to measurement of lifetime ECLs.

3.3.1 Lifetime Probability of Default

With the one-year-ahead PD model in place (Section 3.2), we can expand the time horizon, and using the methods of survival analysis can estimate lifetime PDs and loss rates.²⁹

Assume that loan k was issued with a maturity of n years, as depicted in Figure 6. Let

Figure 6: Loan Lifetime Evolution



T_k be a random variable that represents the time in years to first default of the 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 $PD_{k,0}, PD_{k,1}, \dots, PD_{k,n-1}$ can be predicted using equation (1) estimates in 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 $PD_{k,t}$, with $t = 0, \dots, n - 1$, is a conditional probability:

$$PD_{k,t} = \mathbb{P}(T_k \leq t + 1 \mid T_k > t).$$

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

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

where

$$\begin{aligned} \mathbb{P}(T_k > t) &= \mathbb{P}(T_k > t \mid T_k > t - 1) \mathbb{P}(T_k > t - 1) \\ &= \mathbb{P}(T_k > t \mid T_k > t - 1) \mathbb{P}(T_k > t - 1 \mid T_k > t - 2) \dots \mathbb{P}(T_k > 0) \\ &= (1 - PD_{k,t-1})(1 - PD_{k,t-2}) \dots (1 - PD_{k,0}) \\ &= \prod_{m=0}^{t-1} (1 - PD_{k,m}), \end{aligned}$$

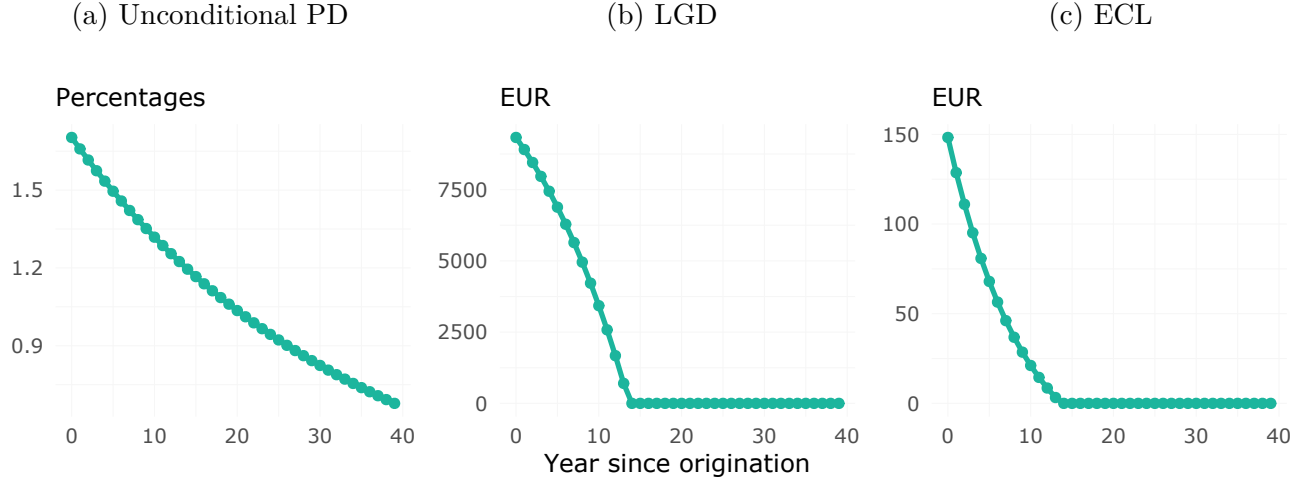
so that

$$\mathbb{P}(T_k \leq t + 1, T_k > t) = PD_{k,t} \prod_{m=0}^{t-1} (1 - PD_{k,m}). \quad (2)$$

²⁹Our lifetime ECL formulae are like Buesa and others (2019), although the latter paper purely focuses on IFRS 9 without estimating PDs at the loan level, and with no regard for macroprudential BBMs.

As an example, we depict the evolution of unconditional PD throughout a loan’s life cycle in Figure 7(a), computed using model estimates in Table 5. The figure shows that the probability of default at a particular year declines toward the end of the loan’s lifetime. This can be explained by two features: (1) the coefficient of residual maturity is positively related to one-year-ahead PD (see Table 5); and (2) naturally, the probability of survivorship decreases toward the end of the loan contract.

Figure 7: Point-in-Time Parameters over the Life cycle of a Loan



Note: (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 percent haircut to collateral value at the time of default (downturn LGD); (c) ECLs are calculated as pointwise products of corresponding unconditional PDs and LGDs.

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

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

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

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

3.3.2 Loss Given Default

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

$$\text{LGD}_{k,t} = \max \{ \text{EAD}_{k,t} \cdot (1 + C) - \text{CLLT}_{k,t}, 0 \}, \quad (5)$$

where $EAD_{k,t}$ is the exposure size at the time of default and $CLLT_{k,t}$ is collateral value. We assume that a fraction $C = 5\%$ of the $EAD_{k,t}$ 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. Note that equation (5) implicitly assumes zero probability of loan recovery after a default occurs, however, extensive testing indicated that the inclusion of 50 percent cure rate does not materially affect the results.

Figure 7(b) showcases the evolution of the LGD parameter since the loan's inception, which is computed by assuming an amortization schedule. At the beginning phases of the loan contract, LGD is positive and large, since the loan is not amortized yet. Over time, LGD vanishes to zero, as the loan is amortized and becomes small relative to the value of pledged collateral. By definition, the oLTV parameter is heavily linked to the collateral value and exposure at default, affecting 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:

$$ECL_{k,t} := LGD_{k,t} \cdot PD_{k,t} \prod_{m=0}^{t-1} (1 - PD_{k,m}). \quad (6)$$

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

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

$$ECL_{k,n}^{LT} := \sum_{t=1}^n \left[\underbrace{(1 + i_k)^{-t}}_{\text{Discount factor}} \underbrace{LGD_{k,t}}_{\text{LGD of year } t} \underbrace{PD_{k,t} \prod_{l=0}^{t-1} (1 - PD_{k,l})}_{\text{Unconditional PD of year } t} \right]. \quad (7)$$

The term $(1 + i_k)^{-t}$ denotes the k -th loan's discount factor, where i_k corresponds to the loan's interest rate.³⁰

³⁰Since we are mostly interested in lifetime credit risk at each loan's origination, we assume away any interest rate dynamics, which is hardly predictable for long-term loans, spanning 20-30 years.

3.3.4 Computation of Lifetime Credit Risk at Origination

Equations (2)-(7) lay theoretical foundations for the assessment of lifetime credit risk. As our framework relies on prediction of one-year-ahead PDs 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 amortization and macroeconomic conditions.

For each mortgage that was issued between 2004 and 2020, we observe initial loan and household characteristics and construct a hypothetical amortization schedule. All mortgages and other household loans, including leases and consumer credits, are amortized to maturity in accordance with the annuity payment scheme so that outstanding amounts and cLTV ratios are adjusted accordingly.³¹ Household characteristics, like family 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 uses 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 $\text{PD}_{k,t}$. Lastly, lifetime PDs and ECLs are estimated using equations (3) and (7).

This section described our mortgage risk modeling approach, which builds a framework for the evaluation of lifetime credit risk by using the one-year-ahead PD model. Now, with our modeling framework in place, we can assess the efficacy and adequacy of Lithuania’s BBMs.

4 Assessment of Borrower-Based Measures

Previously we discussed that ASN measures have been in place in Lithuania since 2011; however, their efficacy may be questionable, considering that domestic housing credit market imbalances have emerged. Specifically, in 2022, there was an identified mortgage credit overflow of 15 percent, casting doubt on whether the policy toolkit’s parametrization is binding enough, especially during the period of low interest rates. If not, this could be tackled by a recalibration of BBMs – tightening the DSTI limit or other measures, such as the term maturity or the 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 with further tightening the already-stringent LTV cap. Nonetheless, the right DSTI cap is unclear from the perspective

³¹Amortization schedules need to be constructed for other household loans as well, since the LTV-assessment exercise for secondary mortgages (Section 5) uses the DSTI metric, which includes all household loans.

of credit risk. In this section we use Section 3’s modeling framework to 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 2000s preceding the GFC, the Lithuanian household credit portfolio grew at a whopping 55 percent rate on an average annual basis. This process was enabled in part by the then-low financial depth of the economy, and fueled by abundant funding from abroad via Nordic bank subsidiaries that were competing against each other and offering low credit margins (Karmelavičius and others, 2023). As Figure 8(a) and (b) show, the competition resulted in a gradual deterioration in lending standards. Specifically, around 2008, a quarter of new mortgage issuance had LTVs as high as 100 percent. A similar dynamic took place for mortgage DSTI ratios and durations, as borrowers tried to compensate for decaying housing affordability with higher indebtedness and ever longer maturities.

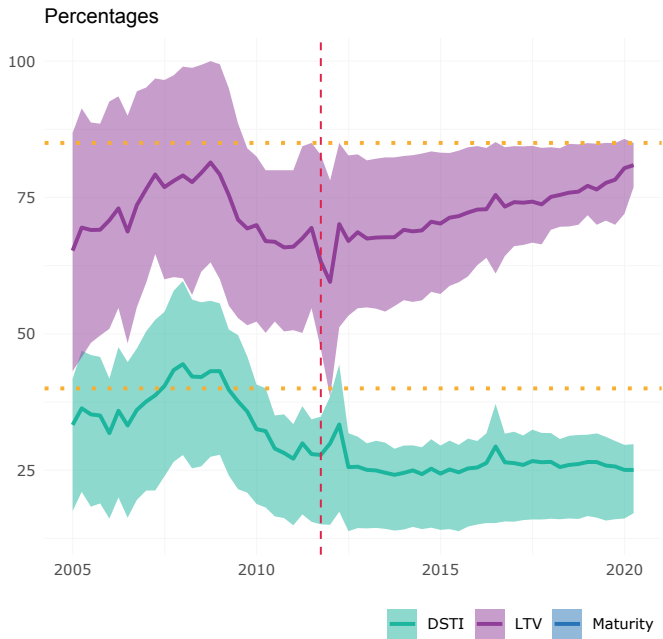
We used our modeling framework from Section 3 to evaluate the underlying credit risk of individual mortgages that were issued preceding the GFC. Figures 8(c) and (d) show that the average at-origination lifetime PD gradually rose along with DSTI, LTV, and maturity metrics and reached 12 percent around 2008. Essentially, 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 percent, 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 and others (2016) and Reichenbachas (2020) show that had the LTV requirement of 85 percent been in place in Lithuania in the 2000s, 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, 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 that would have breached any of the ASN requirements, we censor its maturity, DSTI, and LTV metrics using the respective limits of 30 years, 40 percent and 85 percent. We do so by first limiting the maturity of a given mortgage and recalculating its DSTI ratio and then reducing the loan amount if DSTI and LTV caps were violated. Using this synthetic parametrization for each loan issued prior to 2011, we predict its one-year-ahead PD, lifetime PD, and ECL rate.³²

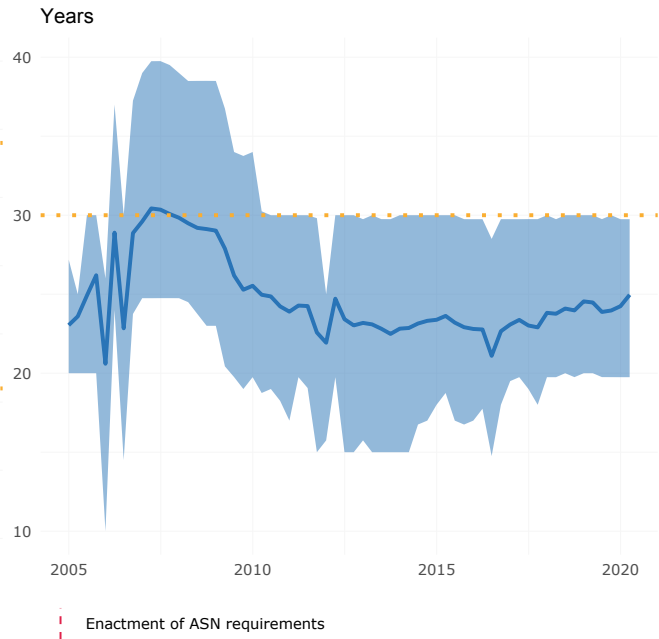
³²This computation is a mere sensitivity analysis that does not take into account the probable outcome that some loans would have been issued later, or not issued at all, if ASN limits were present. Also, we do not account for possible macroeconomic feedback effects through reduced house price, credit, and economic growth.

Figure 8: At-Originatioin Risk Parameters for New Mortgages

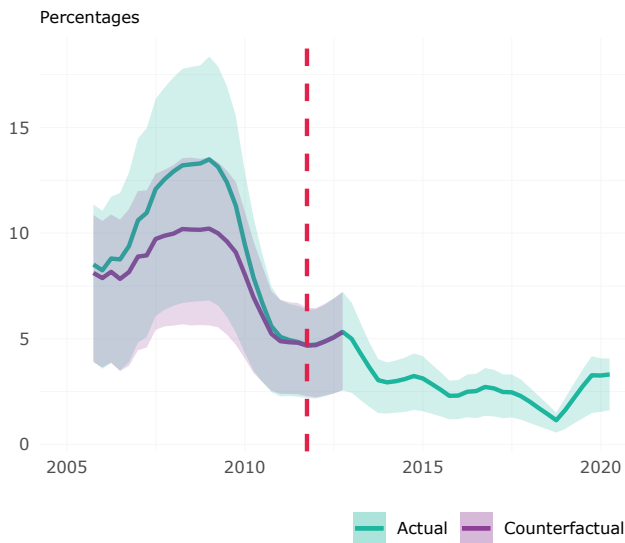
(a) LTV and DSTI



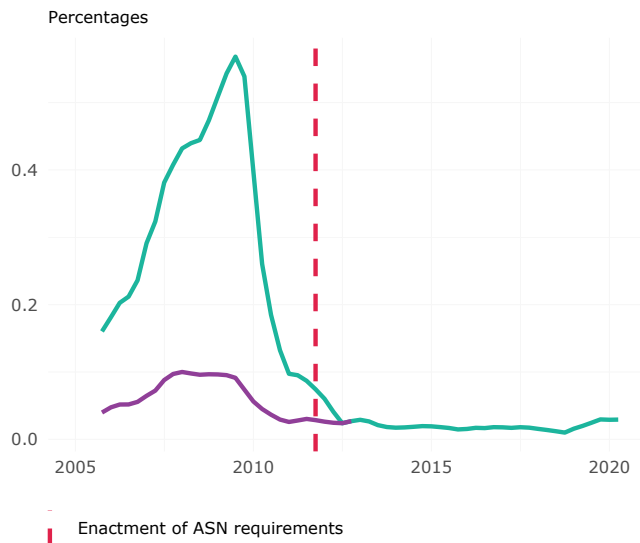
(b) Maturity



(c) Lifetime PD



(d) Lifetime ECL rate



Note: (a) and (b): The 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 PDs and ECL rates are estimated at the moment of mortgage origination using an amortization 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 one-year window; (d) The ECL rate is calculated as a ratio of aggregate ECLs to sum of new mortgages.

The at-origination counterfactual estimates are represented 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 2000s, the average credit risk of individual mortgages would have been significantly lower: lifetime PD by 2 p.p. and the lifetime ECL rate by 0.3 p.p. This

implies that the BBM package, if implemented, would have reduced the mortgage ECL rate by 78 percent in relative terms. Additionally, as people would have taken smaller loans because of such hypothetical regulation, the mortgage portfolio would have been at least 24 percent smaller. By combining the lower relative loss rate with the lower mortgage volume, we compute that aggregate mortgage portfolio losses for the banking sector would have been around 83 percent ($= [1 - (1 - 0.78)(1 - 0.24)] \times 100\%$) smaller.³³ This estimate of the ASN package’s impact on Lithuanian banking losses exactly coincides with Matkėnaitė and others (2016) who consider only the LTV limit. The results are summarized in:

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 percent smaller than those experienced by Lithuania’s banking sector during the crisis.*

The finding does not consider 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.

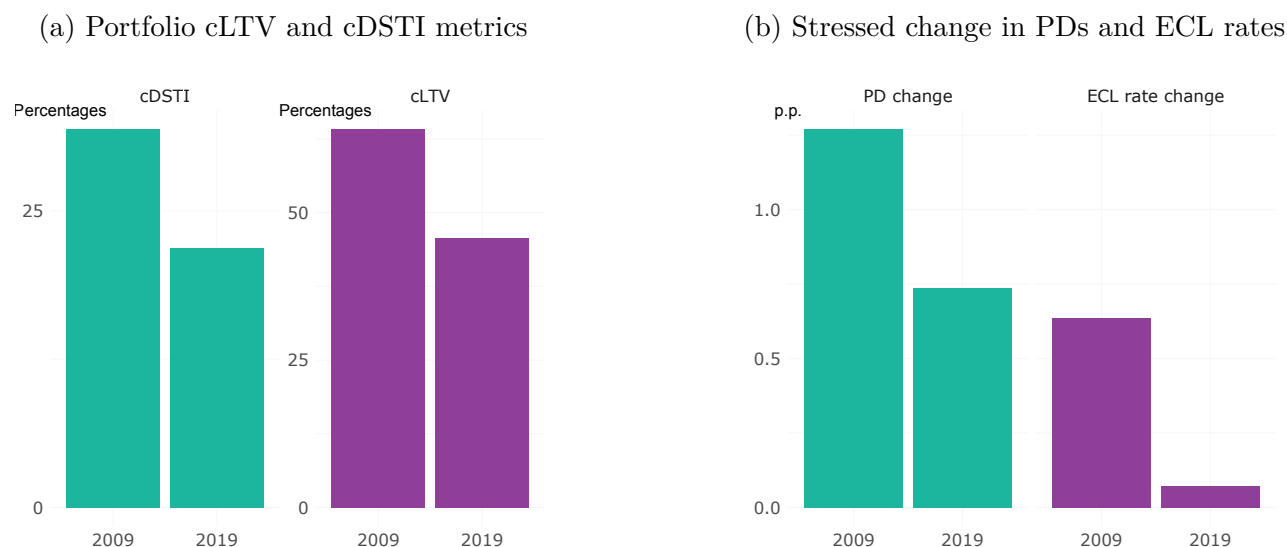
4.1.2 Post-GFC period: ASN Framework and Borrower Resilience

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, the post-GFC period can be characterized by lenders’ self-corrective behavior, which may have stemmed from either a sudden change in sentiment or realization 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 and others, 2016; Reichenbachas, 2020). Notwithstanding, the limits included in the rulebook set a standard for all market participants, including both creditors and debtors, suppressing the righthand tail of the risk distribution and thus curtailing the procyclicality of risk appetite. This is vividly portrayed in Figure 8(a) and (b), wherein after 2011, the growth in the 75th percentile of at-origination LTVs and maturities is limited by the respective BBMs.

Our credit risk model estimates suggest that in the 2010s, lifetime PDs and ECL rates gradually declined and became significantly lower than the pre-GFC period, thus the risk profile of new mortgage issuance improved (Figure 8c and d). Because changes in mortgage flow composition accumulate to changes in stock, mortgage portfolio current DSTI ratios and current LTVs substantially declined, as depicted in Figure 9(a). On the basis of portfolio data in 2009 and 2019, we

³³In addition to that, we utilize 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 percent ($= [1 - (1 - 0.83)(1 - 0.24)] \times 100\%$) smaller mortgage portfolio losses during the GFC – a bit larger estimate than 83 percent.

Figure 9: Mortgage Portfolio Quality and Resilience to Stress: 2009 and 2019



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

conducted a stress test, which shows that mortgage portfolio credit risk parameters are now less sensitive to adverse changes in the economic environment (Figure 9b). As ASN regulations curb risk-taking behavior by disallowing BBM-related parameters from being over the limit, they play an important role in keeping lifetime credit risk anchored and borrowers more resilient to negative shocks of both an idiosyncratic and aggregate nature.

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

The finding supplements those of Reichenbachas (2020), who shows that the cap on the LTV ratio reduced credit growth, especially throughout 2016-19 when the limit became more binding. In essence, BBMs can be effective in limiting credit risk and boosting resilience and also curbing credit growth. On the other hand, recent house price overvaluation and credit overflow imply that the policy toolkit's current parametrization does not eliminate misalignments altogether.

4.1.3 Comparison of Instruments in Predicting Default

The discussion above about Findings 1 and 2 illustrates that the ASN package as a whole can be effective in containing credit risk; however, the efficacy of individual instruments is not yet clear. This subsection discusses which of the BBM-related variables is best at predicting whether a housing loan will default and thus is the most suitable policy target to contain risk. We test how much additional discriminatory power each variable generates in terms of the AUROC statistic for

the one-year-ahead PD model.³⁴

Specifically, we test 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 as well is included in 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 percent interest rate has an effective DTI limit of 9.³⁵ Second, although the DSTI limit is the most prevalent income-related indebtedness measure in Europe, some countries use DTI or LTI ratios to limit overall household indebtedness – Denmark, Ireland, and Norway 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 BBMs in determining mortgage default, we fit 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, and interest rate, and finally estimate the full model. For each model, we implement the five-fold cross-validation procedure and compile AUROC statistics in Table 3.

Table 3: AUROC Statistics for Different One-Year-Ahead PD Model Specifications

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

Note: AUROC estimates are compiled using a five-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) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \beta_1^\top \varphi(\text{oBBM}_k)$;
- (ii) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \beta_1^\top \varphi(\text{oBBM}_k) + \beta_2 \text{Maturity}_{k,t}$;
- (iii) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \beta_1^\top \varphi(\text{oBBM}_k) + \beta_2 \text{Maturity}_{k,t} + \beta_3 \text{oLTV}_k$;
- (iv) $\text{logit}(\text{PD}_{k,t}) = \beta_0 + \beta_1^\top \varphi(\text{oBBM}_k) + \beta_2 \text{Maturity}_{k,t} + \beta_3 \text{oLTV}_k + \beta_4 \text{IR}_{k,t}$;
- (v) Full model (equation 1).

Specifications oLTV-(ii) and oLTV-(iii), as well as oMaturity-(i) and oMaturity-(ii), and oLTV-Full and oMaturity-Full are overlapping, hence the respective cells contain identical AUROC statistics.

³⁴We focus only on the PD component of the credit risk, because we do not have actual loss data to empirically estimate the relationship between BBM-related variables and the factual LGD rate. Instead, our modeling framework computes the LGD based on a loan’s features (equation 5), primarily driven by the LTV ratio, which is consistent with the literature (e.g. Gross and Población, 2017; Ampudia and others, 2021).

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

Estimation results suggest that model specifications containing income-related indebtedness measures ($\text{oD(S)TI}^{(*)}$) have significantly higher discriminatory power compared with models that have the oLTV ratio or maturity term.³⁶ This is in line with the result of Gross and Población (2017) and related literature, where authors show that the DSTI ratio is more important for determining the PD, while LTV is the primary determinant of the 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, discussed in the next subsection. Interestingly, under the full model specification, the predictive superiority of $\text{oD(S)TI}^{(*)}$ indicators diminishes. This is because the full model incorporates other characteristics, such as household income and credit history, which are strong determinants of future default.

Looking closer at the predictive accuracy within the $\text{oD(S)TI}^{(*)}$ group reveals 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 percent 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 the AUROC statistic for both the empty model (i) and the full specification. First, 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). Second, 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. Viewed from the opposite side, where the empty model contains only the relevant $\text{oD(S)TI}^{(*)}$, the oDSTI 's predictive advantage is stronger.

The discussed results can be applied to BBMs and generalized as the following finding:

Finding 3: *Effective containment of 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 for controlling the loss given default parameter.*

³⁶ oLTV 's effect on mortgage PD is significantly lower across model specifications. This may be explained by the lack of intention to default strategically in Lithuania, which has a full recourse system. Further, the oLTV variable in the full model is less statistically significant than the oDSTI variable, and its coefficient is evidently smaller – a 1 p.p. increase in oLTV has a far lower effect on PD than the same increase in oDSTI (Table 5). Nonetheless, the oLTV ratio is a crucial factor, as it directly affects the ECL through the LGD parameter (equations 5 and 6).

4.2 Recalibration Toward Tighter Stance

This subsection explores various policy combinations of DSTI caps and maturity limits that would increase the tightness of the 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 the headline DSTI and the stressed DSTI*, since their tightening would be less distortionary and more risk-targeted via containment of mortgage PD compared with a more stringent LTV policy (see Section 2.4 and Finding 3). Because a lower DSTI^(*) cap would incentivize new borrowers to take out loans with extended maturities, we analyze the DSTI^(*) cap in combination with the maturity limit and their joint impact on mortgage PDs and ECL rates.

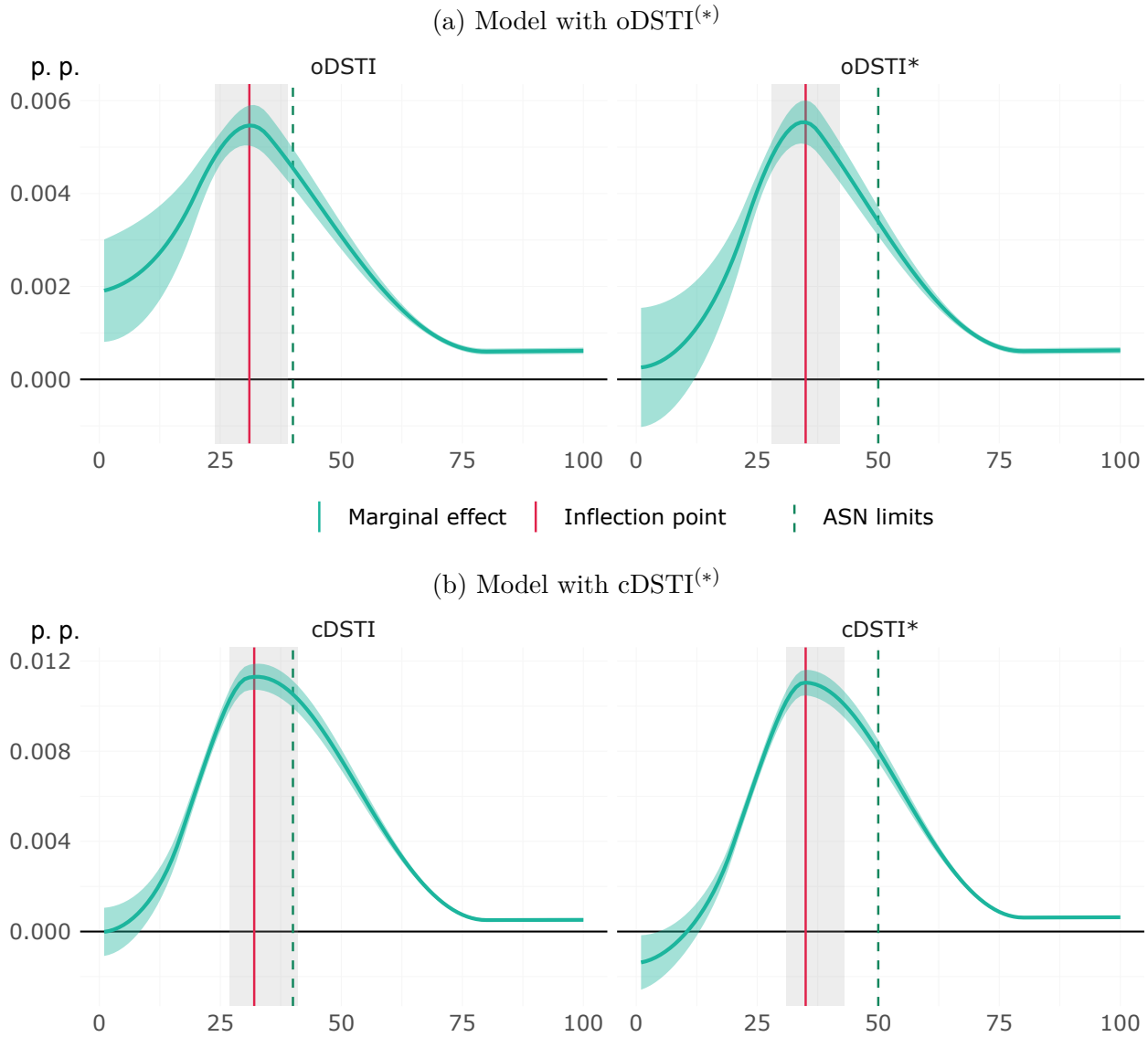
4.2.1 Adequacy of DSTI^(*) Regulation

The observed credit overflow poses the question of whether the regulatory stance was tight enough during the low-rate period. As previously discussed, the DSTI^(*) limit is the most sensible option for further tightening the BBMs. Nonetheless, the right DSTI^(*) limit from a risk-based perspective is unclear. Examining the relationship between the DSTI^(*) metric and default probability addresses this issue. 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 and others (2015), Mihai and others (2018), Kelly and O’Toole (2018), Nier and others (2019), de Haan and Mastrogioacomo (2020), and Andries and others (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^(*), the PD responds more abruptly to changes in these variables, whereas at other levels, 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.

The chart shows that the point estimate, represented by the 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 percent, debt service is very small compared with 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 percent with confidence interval of [24, 39] and 35 percent [28, 42] for the stressed oDSTI*.

Figure 10: Average Marginal Effects of DSTI^(*) on One-Year PD



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

Note: The green area around the green curve corresponds to the 95 percent confidence interval for marginal effect estimate. The gray area around the red vertical line corresponds to a 95 percent 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 quickly, a creditor or the regulator may want to limit the oDSTI^(*) values even before, so that PD growth does not reach this highpoint.³⁷

³⁷Some authors find the oDSTI “optimal” where the marginal effect curve takes off the zero axis, i.e., impact of oDSTI becomes significantly positive (e.g., see Nier and others, 2019). In our case, it already happens at 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.

Nonetheless, the ASN framework’s current parametrization ($\text{oDSTI} \leq 40\%$ and $\text{oDSTI}^* \leq 50\%$) is already beyond those inflection points, which are obtained using the PD model ($\text{oDSTI} \sim 31\%$ [24, 39] and $\text{oDSTI}^* \sim 35\%$ [28, 42]), suggesting that there is room for tightening 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 the current $\text{cDSTI}^{(*)}$ ratio is used in place of at-origination $\text{oDSTI}^{(*)}$ (see Table 6 of Appendix A).³⁸ Figure 10(b) shows that while the resulting marginal effects are now stronger compared with the baseline $\text{oDSTI}^{(*)}$ model, the nonlinear shape is more or less preserved. Regarding inflection point estimates (the red vertical lines), the transition from oDSTI to cDSTI does not change them. However, we can see from Figure 10(b) that the cDSTI inflection interval (gray area) overlaps the current ASN 40 percent regulatory limit, whereas the stressed DSTI^* limit is still far 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. Essentially, different model specification estimates, based on 2012-20 data, which coincided with the low-rate period, suggest that $\text{DSTI}^{(*)}$ caps were on the loose side, especially the stressed DSTI^* limit.

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

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

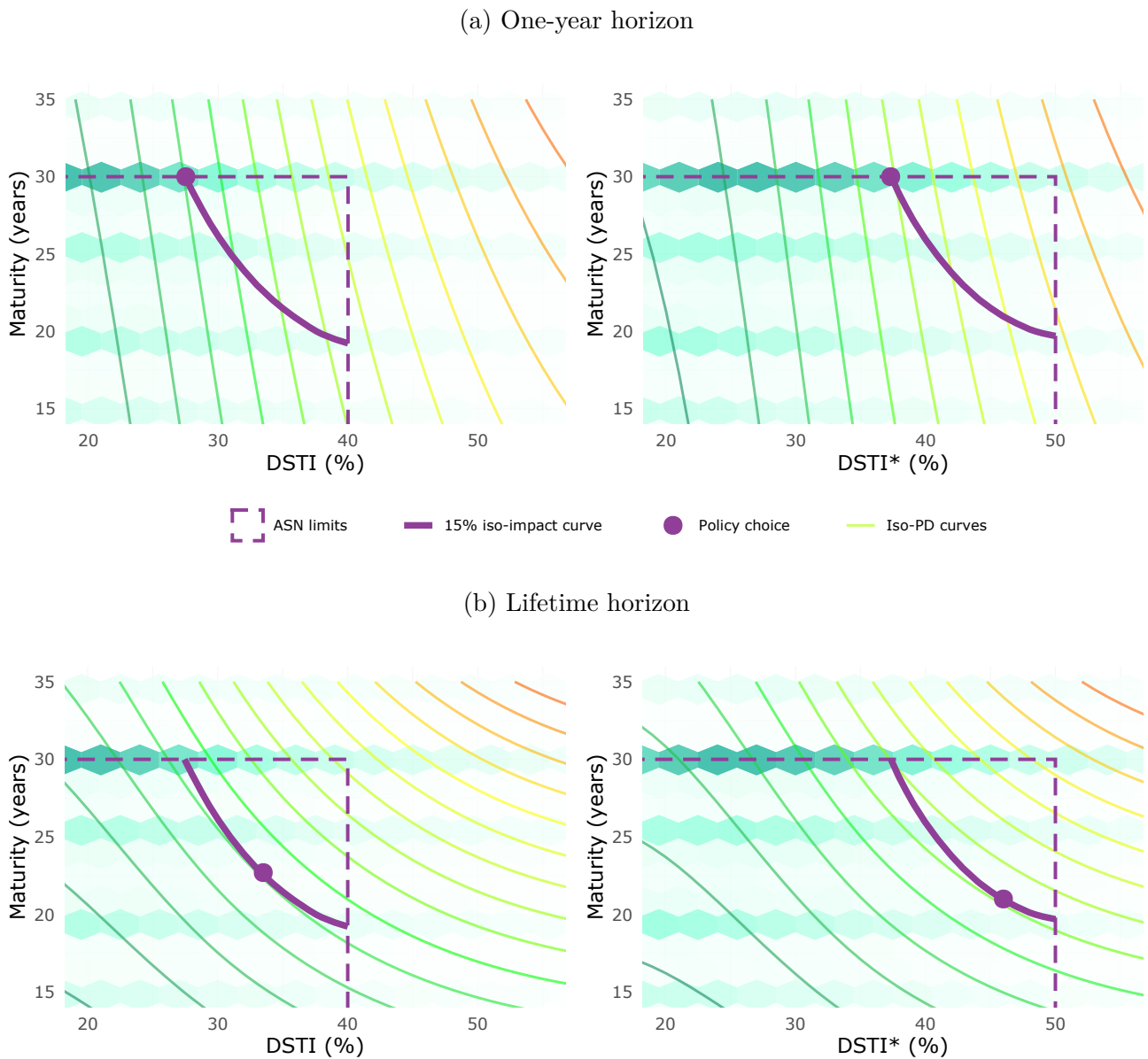
4.2.2 Combination of $\text{DSTI}^{(*)}$ and Maturity Limits

While the previous subsection examines the nonlinear relationship between $\text{DSTI}^{(*)}$ 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 $\text{DSTI}^{(*)}$ metrics in conjunction with maturity affect mortgage default.³⁹ We start by looking at the one-year-ahead PD and later expand into the lifetime PD framework.

³⁸See footnote 33.

³⁹The model that used for this analysis contains the current $\text{cDSTI}^{(*)}$ and residual maturity variable, instead of the at-origination $\text{oDSTI}^{(*)}$ and initial maturity. However, as we compute PDs at the origination of a loan agreement, current metrics exactly coincide with their at-origination values. The reason we choose the $\text{cDSTI}^{(*)}$ variable is that it better resembles the riskiness of a loan throughout its lifespan, rather than the nonchanging $\text{oDSTI}^{(*)}$ variable.

Figure 11: Iso-PD and Iso-Impact Curves for Combinations of DSTI^(*) and Maturity Limits



Note: The dashed purple rectangle represents existing caps on maturity and DSTI^(*). The solid purple curve corresponds to possible combinations of maturity and DSTI^(*) limits that would reduce new mortgage flow by 15 percent (see Appendix C for details). The 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). The hexagon-shape points mark the actual distribution of new mortgage loan characteristics.

(a) One-Year Horizon

Suppose a regulator chooses a certain level of mortgage PD that is within 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 visualized 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

the PD level it represents.

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 that appropriate level is, rendering such process highly subjective. The Section 2’ analysis of misalignments shows that there is a 15 percent 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 percent. From a policy effectiveness perspective, each policy combination on that iso-impact curve is equally capable of 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 with the current policy limit of {40%, 30y.}. Note that the construction of this iso-impact purple curve is subject to household behavioral assumptions, and is described in Appendix C.

By 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 a risk perspective. This is exactly where iso-impact and iso-PD curves come together, as visualized in Figure 11(a). 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 percent, while minimizing micro-credit risk, would be to reduce either the DSTI limit to around 30 percent, or the stressed DSTI^{*} to 40 percent, leaving the maturity limit of 30 y. unchanged.⁴⁰ 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 percent may be a better choice. Effectively, such policy move would make the DSTI limit of 40 percent obsolete, as it would be shadowed by the new $DSTI^* \leq 40\%$ cap.⁴¹

(b) Lifetime Horizon

It is sensible to assume that loans with longer maturities are more likely to default over their lifespan even at reasonable levels of DSTI^(*) – just as a car is more likely to crash on longer journeys even when driving at a reasonable speed. Therefore, it is necessary to consider the duration of

⁴⁰The purple points of Figure 11(a) 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.).

⁴¹The limit of $DSTI \leq 40\%$ would become nonbinding since $DSTI^* \leq 40\%$ would be a tighter measure. This can be seen from this inequality: $DSTI^*(DTI, \max\{i, 5\%\}) \geq DSTI(DTI, i)$.

a housing loan by using the lifetime PD framework rather than solely using the one-year-ahead model.

The definitional equations (3) and (4) show that lifetime PD increases monotonically along with increasing loan maturity n , if $DSTI^{(*)}$ and other variables are constant. This is the reason the 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 the $DSTI^{(*)}$ 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 the loan's duration and $DSTI^{(*)}$ metric becomes moderate and the iso-PD curve map in panel (b) is more convex.

Minimization of lifetime PD while targeting the desired policy impact of a 15 percent credit reduction is now in favor of reducing both the $DSTI^{(*)}$ cap and the maturity limit. This is shown in Figure 11(b), where an iso-PD curve for $DSTI^{(*)}$ and maturity is tangential 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 aimed at achieving some desired outcome of credit volume reduction while minimizing individual mortgage credit risk. If our analysis focuses 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 suboptimal ASN limits for income-based variables. If we expand our analytical horizon and look at how mortgage loans perform over their whole lifespan, the minimal-risk policy solution would be to reduce both the $DSTI^{(*)}$ cap and the maturity limit. This subsection's results can be summarized 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, minimization 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 percent may be questionable, therefore the regulator may either reduce the $DSTI^*$ cap to around 40 percent, or limit both $DSTI^*$ and maturity to around 45 percent and 20y., respectively. While both options would reduce mortgage credit flow by approximately 15 percent and effectively close the credit gap, the latter joint tightening of $DSTI^*$ and maturity limits would minimize lifetime credit risk for individual housing loans.

However, it is of the utmost importance to realize that mortgage interest rates are on the rise due to a sharp change in monetary policy stance, which is considered in the above analysis. Based on Karmelavičius and others (2022), a 3 p.p. increase in mortgage rates could translate into a 12 percent decrease in 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

DSTIs from 27 percent to 30 percent, effectively making the 40 percent cap binding for some fraction of borrowers. This suggests that as interest rates continue to rise, current parametrization of ASN regulation will become more binding and effective in stabilizing 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 the current LTV ratio of a household’s first, and still active, mortgage is higher than 50 percent, the household may finance an additional home purchase with a secondary mortgage of only up to a 70 percent LTV limit. For borrowers whose first active mortgage loan has a cLTV that is lower than 50 percent, the secondary mortgage LTV ratio must be lower than 85 percent. While this new regulation was not intended to impact 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 illuminates 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, it shows how secondary mortgages are different in their risk profile compared with single mortgage loans.⁴² Second, the section outlines a secondary mortgage LTV limit micro-calibration exercise to equalize the credit risk of secondary loans to single mortgages.

5.1 Probability of Default Differential

Section 2 discusses that secondary mortgages are riskier, as they tend to default around 50 percent 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 the DSTI ratio is a major determinant of loan default probability, this naturally translates into higher factual default rates on secondary mortgages. With 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 percent; hence, risks are contained.

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. The one-year PD modeling results that are tabulated in Table 5 of Appendix A answer this. Across all specifications, a mortgage

⁴²We call a housing loan “single”, if it is solitary within a household’s debt pool at a given point in time, i.e., there are no other mortgages. A first mortgage is not necessarily single, since at a given point there may exist a secondary mortgage that originated later than the first loan.

loan is statistically significantly more likely to default if the borrowing household has other active mortgage loans. The latter effect's magnitude positively depends on other housing loans' cLTV ratios. 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 nonsingle and secondary at the 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: (1) buy-to-let investment that is subject to risk of loss of rental income, which may be more unstable than labor income; and (2) acquisition of nonprimary residences to which households may be less attached and therefore less inclined to make their debt payments.⁴³

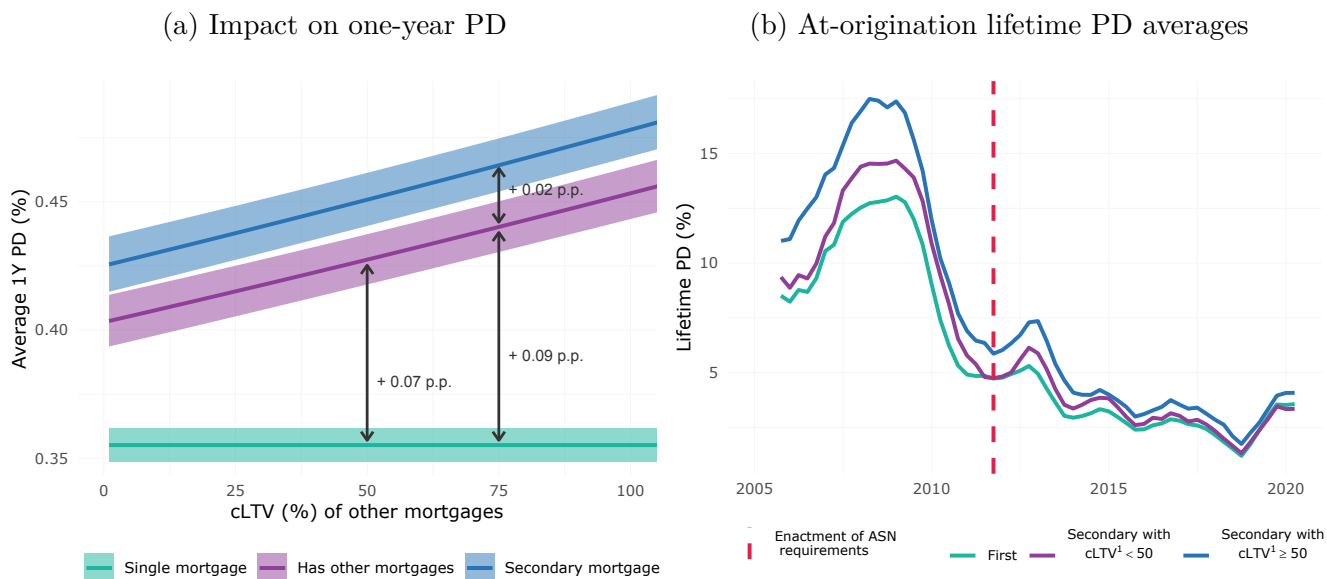
To understand more about the economic rather than the statistical significance of these results, see their probability impact in Figure 12. The green horizontal line in panel (a) marks the average one-year-ahead PD for a mortgage whose debtor household does not have any other mortgage loans, and other 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 nonsingle, i.e., the household has other active mortgage loans. The chart shows 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 percent, the PD differential is only 0.07 p.p. However, when the cLTV ratio of other mortgages reaches 75 percent, the PD differential becomes equal to 0.09 p.p. Moreover, the blue line, which represents a case where the analyzed mortgage is not only nonsingle, 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 percent, may be 0.11 (= 0.09 + 0.02) p.p. more likely to default compared with an otherwise equivalent but single housing loan. The catch is that not only is the secondary mortgage 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 nonperforming. This is in line with a conclusion of Kelly and O'Toole (2018), who find multi-loan borrowers more inclined to default. From a financial stability perspective, secondary mortgages are not only more likely to default individually, but they also impose a negative externality in terms of heightened credit risk for the existing portfolio of housing loans.

While the one-year PD differential of 0.11 p.p. discussed above may seem small, it becomes amplified when moving to a lifetime horizon. Using our modeling framework, we compute at-

⁴³Although at a smaller magnitude, our findings still hold when the cDSTI ratio is used as a PD predictor instead of an oDSTI measure (see Table 6 of Appendix A).

Figure 12: PD Differential of Secondary Mortgages



Note: (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 percent confidence intervals.

origination lifetime PD rates for first and secondary mortgages and depict the average estimates in panel (b) of Figure 12. The purple and blue curves, representing at-origination lifetime PDs for secondary mortgages, lie globally above the green curve, which represents first and single mortgages. Throughout history, the lifetime PD rate has been on average 3 p.p. higher for secondary mortgages compared with that of first mortgage loans. As suggested by the one-year PD model, secondary mortgages whose predecessor-housing loans have $cLTV \geq 50$ percent have an even higher chance to default at least once during their lifespan, with PD difference equal to 3.5 p.p. Although lifetime PDs declined quite significantly in the post-GFC period and continued to decrease after the inception of the ASN framework in 2011, lifetime PD differences between first and secondary mortgages are still nonnegligible, equaling around 0.4 p.p. over the past decade.

To summarize our results, we state the following finding:

Finding 6: *Secondary mortgages (1) are more likely to default over their lifetime compared with an otherwise equivalent but single mortgage loan; and (2) 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.

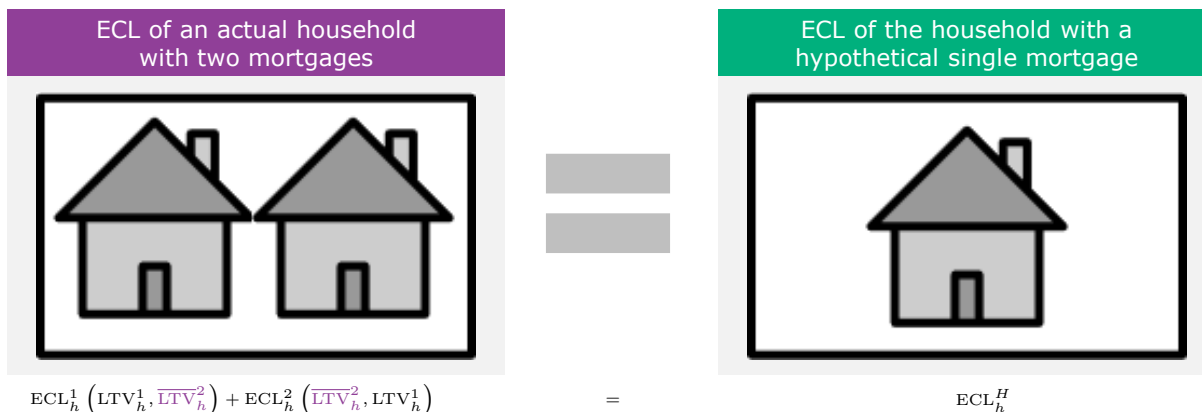
While it is possible to directly affect the secondary mortgage’s LGD² parameter by restricting LTV² at origination, the first mortgage’s LTV¹ ratio and hence the LGD¹ parameter are predetermined.

Here we calibrate the LTV² 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.⁴⁴ 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 a macroprudential nature. This exercise could be used as a starting point in choosing an appropriate macroprudential LTV² limit, as experienced by Bank of Lithuania. First, this section briefly outlines our method, and then explains the results for the one-year and lifetime horizons, using the model framework of Section 3.

5.2.1 Calibration Method

The calibration exercise entails finding a secondary LTV² limit that would equalize 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 LTV² limit such that the aggregate ECL of both loans would be equal to the ECL of a single hypothetical loan (Figure 13).

Figure 13: Calibration of LTV² Limit: Equalization of ECLs



The single-mortgage hypothetical case is used as a benchmark that is compatible with maximum tolerable risk, and thus is parametrized as a limiting case of the ASN requirements: $LTV^H = 85\%$, $DSTI^H \leq 40\%$ 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 ECLs under two horizons: (1) one year; and (2) lifetime. Lifetime ECLs for

⁴⁴Preliminary results of this calibration exercise under the one-year setting were published as a popular commentary (link to article in Lithuanian). The article also contains calibration results that are founded on the micro-macro framework of Gross and Población (2017), thus uses simulated household-level default rather modeled loan-level default. The results are similar and more conservative compared with the ones outlined in this paper, possibly stemming from the fact that household-level modeling of default may better capture the interactions between two different mortgages, their LGDs, and correlated default.

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

household h loan j are defined as:

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

which is practically the same as in equation (7) of Section 3. Note that when we analyze 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, LTVs, 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 in earlier exercises, we use each mortgage loan's amortization schedule to compute how its PD and LGD parameters evolve over its lifespan.⁴⁵ Rewriting equation (5), the 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, the LGD parameter will likely be equal to zero.⁴⁶ As in the previous analyses of this paper, LGD is modeled 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 percent, which matches

⁴⁵For convenience, we assume a zero probability of recovery/cure from the state of default, since extensive testing indicates that nonzero cure probability does not change the results.

⁴⁶In 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 ($\text{LGD}_h^1, \text{LGD}_h^2$) parameters. If we imposed positive correlation between the two LGD parameters, the calibration results would be even stricter, requiring even more stringent regulation of secondary mortgages.

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 with the situation in the 2000s, we regard the scenario (#4) as a baseline for conservative calibration purposes.

By limiting the 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 personalized LTV^2 limit that would prevail at a loan's origination and thus would equalize (lifetime) ECLs 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 $\overline{\text{LTV}}_h^2$ that would solve the following ECL-equating condition:

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

By changing h household's secondary loan oLTV_h^2 ratio, we affect its $\text{PD}_{h,t}^2$ and $\text{LGD}_{h,t}^2$ parameters and therefore the $\text{ECL}_{h,t}^2$. 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 ($\text{PD}_{h,t}^1$, $\text{LGD}_{h,t}^1$, ECL_h^1).⁴⁷

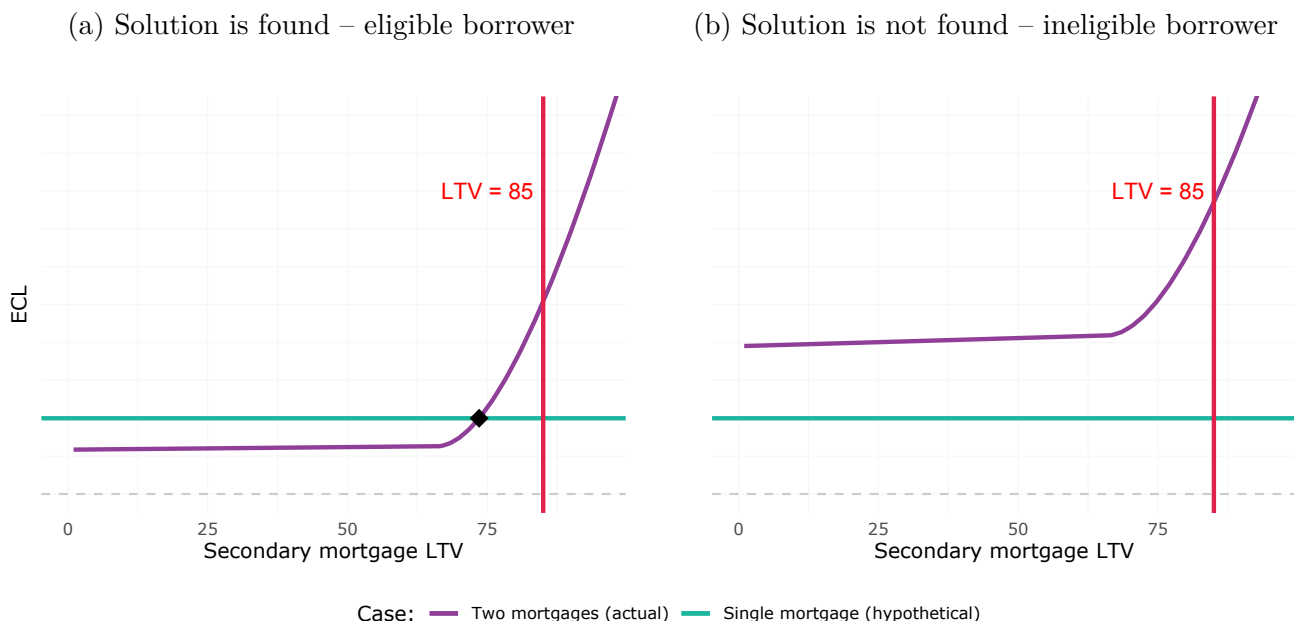
Figure 14 depicts an example of such calibration exercise, using actual historical data of two distinct households. The purple line, which marks each household's aggregate ECL, is monotonically increasing along with the secondary mortgage LTV_h^2 ratio. Interestingly, for both households there is a certain 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 the personalized $\overline{\text{LTV}}_h^2$ limit, which equalizes the credit risk between the two cases. The interpretation is that for household (a), 75 percent 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 the already high DSTI_b or LTV_b^1 ratios, and overall high risk of this particular household.

5.2.2 Calibration Results

With the micro-calibration method explained, this subsection discusses the results of the exercise under one-year and lifetime settings.

⁴⁷Computationally, for each household h , we look for an $\overline{\text{LTV}}_h^2$ that would solve the highly nonlinear equation (8), taking into account the entire amortization 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



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

(a) One-Year Horizon

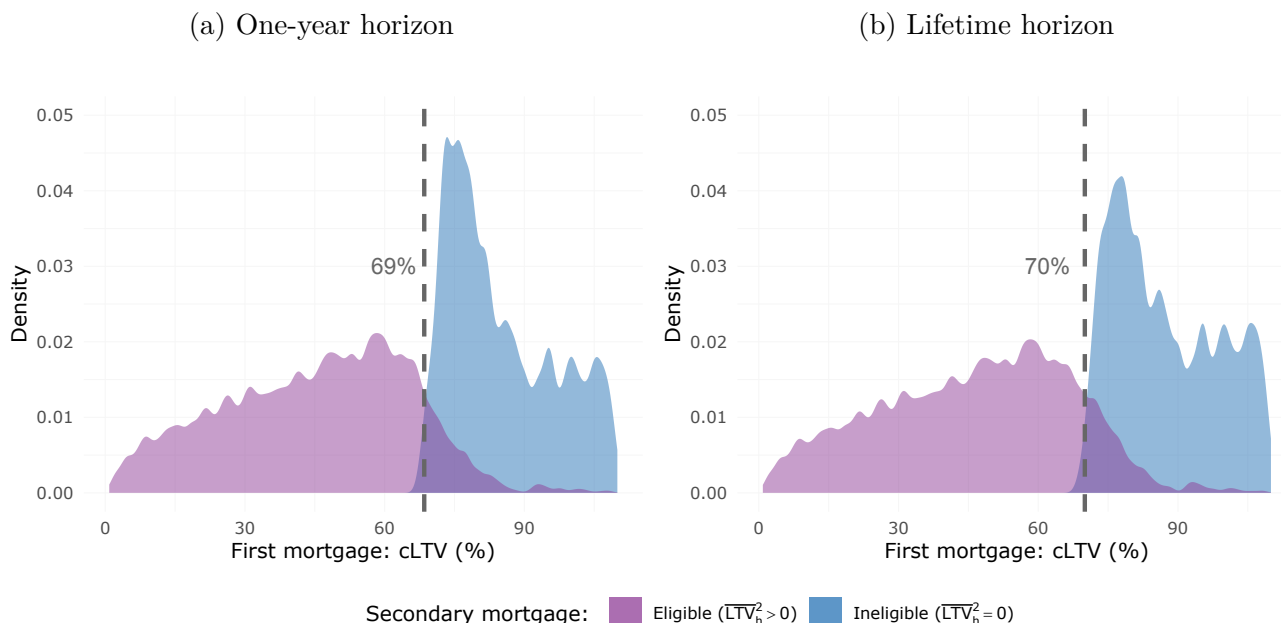
Under the one-year setting we assume: $n_h^j = 1, \forall j \in \{1, 2; H\}$, thus we analyze the ECL one year after the initiation of each secondary loan. The calibration exercise involved finding personalized \overline{LTV}_h^2 limits for around 6,000 households that took out secondary loans during the period 2012-19. Remarkably, 1,500 of the analyzed households should not have been granted a secondary mortgage, as the calibration algorithm did not find a solution within the domain of $\overline{LTV}_h^2 \in (0, 85\%)$. Simply put, their two-mortgage ECL exceeded that of a single hypothetical mortgage, irrespective of LTV_h^2 , as in the example of Figure 14(b).

It is noteworthy that many of the households that should not have been eligible to receive a secondary loan had their first loan LTV_h^1 ratio above 70 percent. This is depicted in Figure 15(a), which shows that most households with an $LTV_h^1 < 70\%$ were eligible, as suggested by our calibration algorithm.⁴⁸

To analyze the resulting personalized \overline{LTV}_h^2 limits, we assume that each 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 that, according to the algorithm solution, were eligible receivers of secondary mortgages,

⁴⁸Note that this threshold $LTV_h^1 < 70\%$ is highly dependent on the assumed Δ house price drop, which in our baseline case is 30 percent. For instance, if we assumed $\Delta = 15\%$, then the LTV_h^1 threshold would be around 85 percent.

Figure 15: Relationship Between LTV_h^1 Distribution and Eligibility for Secondary Loan



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

i.e., $\overline{LTV}_h^2 > 0$ – a truncated set.

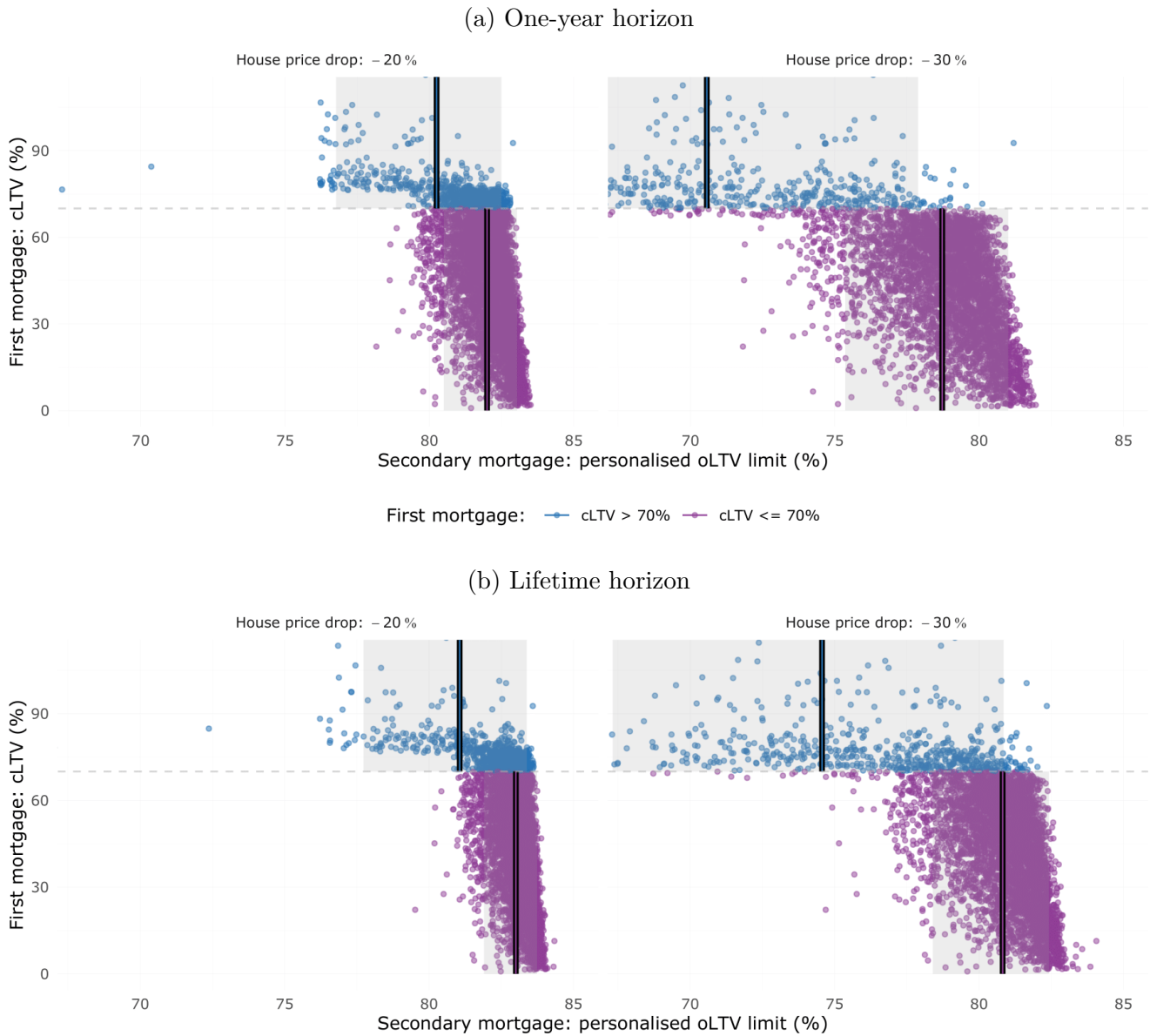
The calibration results under the one-year horizon setting are depicted in scatterplots of Figure 16(a), and they are based on the assumed house price drop (Δ). Each point in the chart represents a combination of the personalized \overline{LTV}_h^2 limit (x-axis) for each household, and the corresponding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

The 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 left of 85 percent. This had been the case even before February 1, 2022, when the new regulation was enacted.

There is a clear negative relationship between the LTV_h^1 ratio of the first mortgage loan and the corresponding personalized secondary mortgage \overline{LTV}_h^2 limit. Essentially, borrowers having still active and relatively unamortized loans could be issued secondary loans with a relatively small LTV^2 ratio and hence a higher down payment. Moreover, the relationship between LTV_h^1 and \overline{LTV}_h^2 is highly nonlinear, as characterized by the kink around $LTV_h^1 \approx 70\%$, which corresponds to the same threshold obtained from Figure 15(a). Many households with $LTV_h^1 > 70\%$ may be eligible for a secondary mortgage, but with, on average, low personalized \overline{LTV}_h^2 limit of 70 percent.

Households whose first mortgage is largely amortized ($LTV_h^1 < 70\%$) may borrow with an \overline{LTV}_h^2 ratio of up to 80 percent.

Figure 16: Personalized Calibration of \overline{LTV}_h^2 Limit



Calibrated \overline{LTV}_h^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%
$cLTV^1 > 70$	83 [82, 84]	80 [77, 82]	74 [71, 81]	70 [66, 78]	83 [83, 84]	81 [78, 83]	78 [73, 82]	75 [67, 81]
$cLTV^1 \in (0, 70]$	84 [83, 84]	82 [80, 83]	80 [78, 82]	79 [75, 81]	84 [83, 84]	83 [82, 84]	82 [80, 83]	81 [78, 82]
$cLTV^1 > 0$	84 [83, 84]	82 [80, 83]	80 [76, 82]	78 [72, 81]	84 [83, 84]	83 [81, 84]	81 [78, 83]	80 [75, 82]

Note: The chart maps a relationship between the personalized \overline{LTV}_h^2 limits and corresponding first loan LTV_h^1 ratios, using different calibration horizons. The vertical lines denote the averaged \overline{LTV}_h^2 limits, with light gray rectangular areas being the 90 percent 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).

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 percent. 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, a 30 percent 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 analyzing 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 like the previous (a) setting. Out of 6,000 households with secondary mortgages, around 1,300, or one-fifth, should not have received a loan, i.e., their personalized \overline{LTV}_h^2 limits are zero. As in one-year setting panel (a), panel (b) of Figure 15 depicts a strong relationship between the eligibility of receiving a secondary mortgage and first mortgage LTV_h^1 ratio, with $LTV_h^1 = 70\%$ being the threshold.

The exact personalized $\overline{LTV}_h^2 (> 0)$ limits along with corresponding predecessor-mortgage LTV_h^1 ratios are depicted in Figure 16(b). Again, all points have $\overline{LTV}_h^2 < 85\%$, and 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 with those when using the one-year horizon. This is clear when 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 ($\Delta = 30\%$), the average \overline{LTV}^2 limit for households with $LTV^1 > 70\%$ is equal to 75 percent under the lifetime setting, wherein the one-year setting it is around 70 percent. Nonetheless, the 90 percent confidence intervals of [66, 78] and [67, 81] are largely overlapping and distant from the headline limit of 85 percent.

Calibration under the lifetime horizon setting results in milder secondary mortgage LTV limits, which may be surprising. Nevertheless, the difference can be explained by the fact that the one-year setting (a) does not fully consider the residual maturity of the first mortgage loan. 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 considers this amortization schedule feature, the one-year setting does not, and thus produces the more stringent calibration results.

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

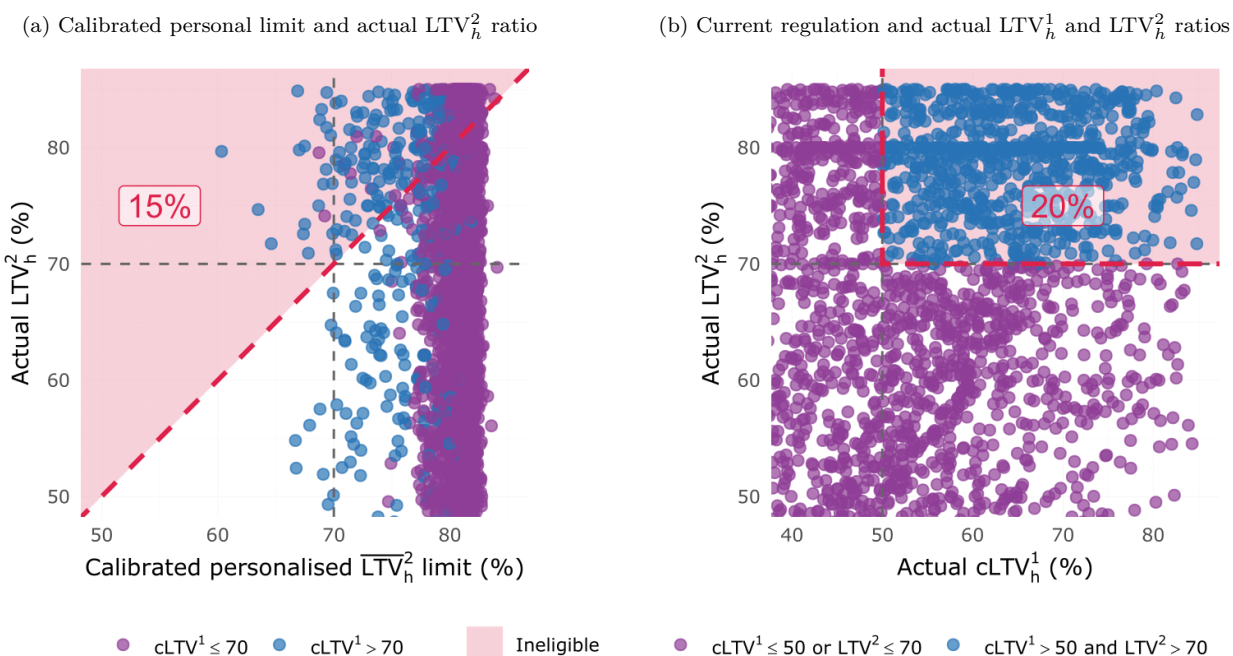
Finding 7: To compensate for the elevated default probability of secondary mortgages, their regulatory LTV limit should be: (1) strictly lower than the headline LTV limit of 85 percent; and (2) differentiated by the borrower’s first mortgage LTV – whether it is below or above 70 percent.

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 percent. This conflicts with their lifetime PD rates being significantly higher than those of single loans. Also, the mere issuance of a secondary mortgage does make the corresponding first loan riskier.

With historical data on secondary mortgage issuance, we can compare their actual LTV ratios to those resulting from our calibration exercise, as graphed in Figure 17(a). It is immediately clear

Figure 17: Counterfactual Impact on Secondary Loan Issuance in 2012-19



Note: The personalized \overline{LTV}_h^2 limits are based on calibration that assumed lifetime ECLs 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{LTV}_h^2 limit. All loan-points above that line, in the red triangle, could be deemed as having LTV ratios that were too high compared with 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 2012-19.

that the positive correlation between the actual LTV ratio and calibrated values is lacking. In many cases, borrowers took out secondary mortgages to finance their additional house purchases with LTVs 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. It is more revealing that there are around 15 percent of all secondary mortgages that should have been issued with lower LTV ratios compared with the calibrated personalized limits, as represented

by the red triangular area above the 45° angle.

Further, panel (b) of Figure 17 reveals that there was no correlation between the actual secondary loan LTV ratio and corresponding first mortgage cLTV ratio. Many borrowers took out a secondary mortgage with a high LTV rate, even when their first mortgage was relatively unamortized with an LTV rate above 70 percent. In fact, the red rectangular area represents around 20 percent of loans that throughout 2012-19 were granted too-high LTV ratios, compared with the new regulation of 2022.

Based on these tendencies and the recent emergence of secondary mortgages, we conclude that the market either has different and perhaps more detailed information on borrower-loan characteristics or a different risk appetite, or simply fails to internalize 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 that our objective function in equation (8) may be rather restrictive, since it compares the ECLs of two loans with a single hypothetical mortgage. To overcome that, we implement an alternative calibration exercise with a laxer objective function of:

$$\text{ECL}_h^2(\overline{\text{LTV}}_h^2, \text{LTV}_h^1) = \text{ECL}_h^H.$$

Essentially, we equalize the ECL of only the secondary loan to the hypothetical single-mortgage case for a fairer comparison. The calibration results depicted in Figure 18 of Appendix A suggest milder secondary LTV limits nearing 80 percent, which are more in line with the observed market practice. However, we deem this approach inferior to our baseline calibration based on equation (8), since it does not consider 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 the first mortgage LTV and the calibrated secondary mortgage LTV limit, as shown by the table below Figure 18.

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 countries including Belgium, Ireland, Norway, and others. Countries including Finland, Iceland, and Luxembourg implicitly have similar regulations, where exemptions are made for first-time buyers rather than explicitly restricting investors.

Although our baseline calibration results suggest that the secondary mortgage LTV limit should be around 75 percent [67, 81] with a first mortgage LTV threshold of 70 percent, the Bank of Lithuania enacted a bit tighter regulation of a 70 percent LTV limit with 50 percent first mortgage threshold. While the 70 percent secondary mortgage LTV limit is within the lower end of

our estimated confidence interval, the threshold limit of 50 percent is significantly lower than 70 percent, which was suggested by our model. 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 the stability of the general economy. As discussed in Section 2, secondary mortgages may exhibit negative externalities and add to market procyclicality. For example, buy-to-let investors are prone to risk-taking behavior and are more likely to buy in a search-for-yield environment, contributing to the boom. As opposed to owner-occupiers, during a housing market correction or when interest rates go up, investors are less inclined to hold on to their properties, potentially causing fire sales, thus accelerating the downturn. Furthermore, since secondary housing loans add undesirable pressure to the formation of imbalances, they may amplify the negative social side effects of BBM regulation on first-time buyers and young families.

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 and others (2016) and Tarne and others (2022). The latter two papers find that buy-to-let investors, who presumably take out secondary mortgages, amplify credit and housing cycles. In particular, Tarne and others (2022) shows 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 BBMs to different classes of borrowers, primarily restricting credit for buy-to-let investors.

Lastly, while macroprudential policy can be used to contain the buy-to-let investors’ segment, it may not be as potent as targeted fiscal measures. In Lithuania, only around half of housing transactions are financed with credit, with buy-to-let investors often financing their house purchases with own funds only. This structural feature limits the effectiveness of macroprudential policy in combating unsustainable housing market developments, including investor-fueled high home price growth. Therefore, fiscal policy measures that target the residential real estate sector, such as appropriately progressive property taxation or stamp duty taxes, can be helpful in curbing housing demand, and thus complement macroprudential policy in aiming to smooth the financial cycle.

6 Conclusions

In response to the recent dynamism of credit and housing markets that were fueled by ultra-low interest rates, this paper takes a second look at the macroprudential BBM framework of Lithuania. Specifically, we assess Lithuania’s ASN parametrization by modeling mortgage-level credit risk throughout each 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.

Efficacy of the BBM framework. Our results indicate that Lithuania’s BBM framework has been effective in significantly reducing the credit risk, and that the banking sector’s mortgage

portfolio is much more resilient to adverse shocks now than before the introduction of the ASN regulation. Additionally, had ASN limits been imposed in the 2000s, the Lithuanian banking sector losses likely would have been minimal during the GFC.

Adequacy of ASN parametrization. While the headline LTV requirement of 85 percent is relatively stringent, with no exemptions for first-time buyers, in retrospect, DSTI and maturity limits could have been tighter during the low-rate period. Taking into account that any reduction in the DSTI cap would induce households to take out loans with longer maturities, our analysis suggests that had the authorities sought to forestall the buildup of imbalances, a joint tightening in the stressed DSTI cap and maturity limit would have been their first-best option. The combined action would have allowed the regulator to achieve the desired policy effectiveness, in terms of reduced flow of credit, while minimizing the lifetime credit risk of housing loans. This would have created policy space for relaxation, which could be used later if overly high interest rates depressed lending and undermined the general economy.

Regulation of secondary mortgages. Secondary mortgages have a higher chance of defaulting compared with otherwise identical but single loans. Further, the mere issuance of secondary loans imposes a negative externality of heightened credit risk on the existing portfolio of housing loans. The historical procyclicality of secondary mortgage issuance suggests a market failure to internalize these risks, which could be addressed by imposing a tighter LTV requirement to keep their credit risk in line with single mortgage loans.

The Bank of Lithuania's decision to set the secondary mortgage LTV limit at 70 percent addresses both the high individual credit risk of secondary mortgages and the negative externalities that this asset class imposes on other market participants and the general economy. While the full effectiveness of the new regulation remains to be seen, there had already been some signs of moderation in secondary mortgage flows even before the interest rate hikes occurred.

This paper's qualitative results on Lithuania's BBMs are broadly in line with the existing literature. For instance, the finding that BBMs are effective in containing credit risk and boosting borrower resilience is also supported by the micro-macro framework of Gross and Población (2017) and related papers, e.g., Jurča and others (2020), Giannoulakis and others (2023). While our DSTI calibration exercise results in quantitatively different estimates from those of Mihai and others (2018) and Nier and others (2019), in principle there is a qualitative agreement on the nonlinear impact of DSTI cap on borrower default.

The insight that secondary mortgages are riskier than single loans is also in line with those of Kelly and O'Toole (2018) and Galán and Lamas (2019), who find multi-loan borrowers and second-home properties to have a higher chance of default. Our policy message on restricting LTVs for secondary mortgage takers is compatible with the agent-based model conclusion of Tarne and others (2022), which states that differentiation of BBM limits to different classes of borrowers may be welfare-improving.

The fact that we assess micro-level credit risk is a strength but also a weakness of our analytical framework. Granular loan data allows for the evaluation of BBM instruments with precision by looking at different market segments, using variation across loans and borrowers, and matching it with their income. On the other hand, overreliance on metrics that measure individual credit risk only, may not show the complete picture, as our framework is not of general equilibrium; thus, it does not capture various feedback loops and negative externalities on a wider scale. Regardless, as this paper conveys, having reliable loan-level information from a credit register is important for any calibration exercise of BBM limits, and in general can support macroprudential decision-making.

To obtain a more complete picture of how credit risk is interrelated with macroeconomic conditions, the analysis could be expanded for a more systemic approach that incorporates not only data on loans, but also on the banking sector and the rest of the economy. One alternative is 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, more ambitious idea is to build a semi-structural framework bearing similarities to the model of Budnik and others (2020, 2023), containing a full-fledged banking sector and a macroeconomic block, possibly allowing for the capture of spillover effects between the mortgage market and the rest of the economy.

Lastly, our analysis was conducted on the cusp of a changing monetary policy stance and using low-interest-rate environment data. Rapidly increasing interest rates concurrently with eroding purchasing power may pose new challenges for borrowers; therefore, additional variation in default data may suggest different conclusions about the appropriateness of the DSTI and stressed DSTI limits. That kind of analysis could form the basis for macroprudential policy frameworks that are contingent on the 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 Paper 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 No. 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 Paper No. 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 Paper No. 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 paper No. 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.
- Biljanovska, N., Chen, S., Gelos, G., Igan, D., Peria, M. S. M., Nier, E., and Valencia, F. (2023). “Macroprudential Policy Effects Evidence and Open Questions”. Departmental Paper No. 2023/002, International Monetary Fund.
- 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 Paper No. 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’Economie*, 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 No. 2469, European Central Bank.
- Budnik, K., Gross, J., Vagliano, G., Dimitrov, I., Lampe, M., Panos, J., Velasco, S., Boucherie, L., and Jancokova, M. (2023). “BEAST: A Model for the Assessment of System-Wide Risks and Macroprudential Policies”. Working Paper No. 2855, 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 No. 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) No. 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.
- Cevik, S. and Naik, S. (2023). “Bubble Detective: City-Level Analysis of House Price Cycles”. Working Paper No. WP/23/33, International Monetary Fund.
- 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 Paper No. 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 Paper No. 16/RT/14, Central Bank of Ireland.
- Galán, J. E. and Lamas, M. (2019). “Beyond the LTV ratio: New Macroprudential Lessons from Spain”. Working Paper No. 1931, Banco de España.
- Gatt, W. (2021). “Housing Boom-Bust Cycles and Asymmetric Macroprudential Policy”. Mimeo, accepted at Journal of Money, Credit and Banking.
- Giannoulakis, S., Forletta, M., Gross, M., and Tereanu, E. (2023). “The Effectiveness of Borrower-Based Macroprudential Policies: A Cross-Country Analysis Using an Integrated Micro-Macro Simulation Model”. Working Paper No. 2795, European Central Bank.
- 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 No. 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. (2023). “What Drove the Rise in Bank Lending Rates in Lithuania During the Low-Rate Era?”. *Baltic Journal of Economics*, 23(2):162–199.
- Karmelavičius, J., Mikaliūnaitė-Jouvanceau, I., and Petrokaitė, A. (2022). “Housing and Credit Misalignments in a Two-Market Disequilibrium Model”. Working Paper No 135 / July 2022, European Systemic Risk Board.
- 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 Paper No. 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.
- Malovaná, S., Janků, J., and Hodula, M. (2023). “Macroprudential Policy and Income Inequality: The Trade-off Between Crisis Prevention and Credit Redistribution”. Working Paper No. 03/2023, 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 No. 9/2022, Bank of Lithuania.
- Mendicino, C. (2012). “Collateral Requirements: Macroeconomic Fluctuations and Macroprudential Policy”. Working Paper No. 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 Paper No. 202110, Banco de Portugal.
- Nier, E., Popa, R., Shamloo, M., and Voinea, L. (2019). “Debt Service and Default: Calibrating Macroprudential Policy Using Micro Data”. Working Paper No. 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 Paper No. 2019/045, International Monetary Fund.
- Ramanauskas, T. (2005). “Bankų kredito didėjimas makroekonominiu požiūriu”. *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 No. 10, Bank of Lithuania.
- Reichenbachas, T. (2020). “Assessing the Impact of Macroprudential Measures: The Case of the LTV limit in Lithuania. Working Paper 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 No. 34, Bank of Lithuania.
- Rutkauskas, V., Kulikauskas, D., and Šumskis, V. (2015). “Lietuvos namų ūkių finansinė būklė ir finansų sistemos stabilumas”. *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.
- Teixeira, A. (2023). “Does Macroprudential Policy Affect Wealth Inequality? Evidence from Synthetic Controls”. *Journal of Financial Stability*, 67:101135.
- Tzur-Ilan, N. (2023). “Adjusting to Macroprudential Policies: Loan-to-Value Limits and Housing Choice”. *The Review of Financial Studies*, (4 May 2023).
- Valderrama, L., Gorse, P., Marinkov, M., and Topalova, P. (2023). “European Housing Markets at a Turning Point – Risks, Household and Bank Vulnerabilities, and Policy Options”. Working Paper No. WP/23/76, International Monetary Fund.

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 and others (2018).

Table 6: One-Year-Ahead PD Estimation Results: *Full* Model (*c* – current)

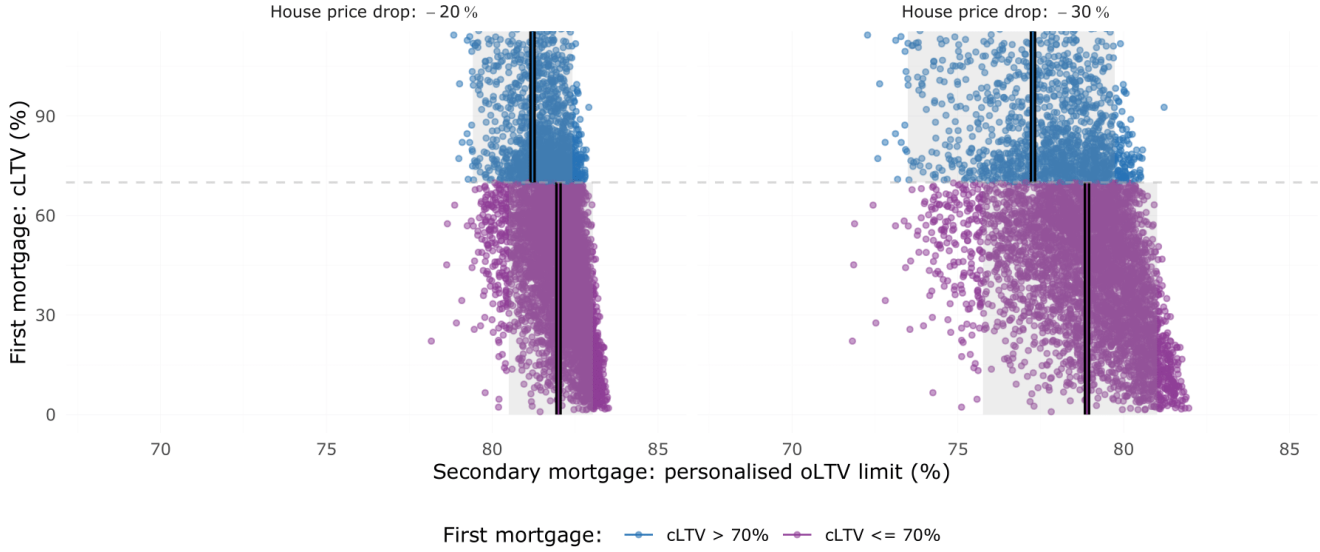
	Model 1	Model 2
Borrower and loan features		
(Intercept)	-6.49 (0.21) ^{***}	-6.49 (0.21) ^{***}
Residual maturity	0.01 (0.00) ^{***}	0.01 (0.00) ^{***}
Has interest rate	0.40 (0.20) [*]	0.39 (0.20)
Interest rate	0.08 (0.00) ^{***}	0.09 (0.00) ^{***}
Secondary mortgage (chron.)	0.09 (0.01) ^{***}	0.11 (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	-1.24 (0.02) ^{***}	-1.23 (0.02) ^{***}
oLTV	0.00 (0.00) ^{***}	0.00 (0.00) ^{***}
Has cDSTI	-1.64 (0.08) ^{***}	
cDSTI cub1	1.51 (0.04) ^{***}	
cDSTI cub2	1.53 (0.12) ^{***}	
cDSTI cub3	1.55 (0.03) ^{***}	
Has cDSTI*		-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} .

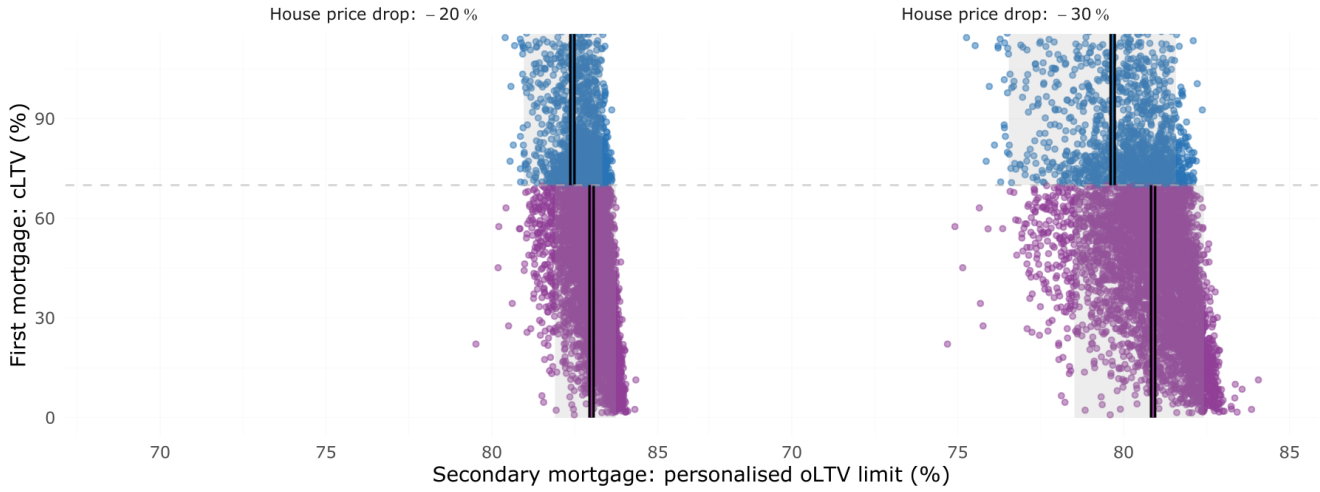
Terms cDSTI^(*) cub1-3 refer to cubic spline polynomials, as in Mihai and others (2018).

Figure 18: Personalized Calibration of \overline{LTV}_h^2 – Alternative Objective Function

(a) One-year horizon



(b) Lifetime horizon



Calibrated \overline{LTV}_h^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%
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]
cLTV ¹ ∈ (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]
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 personalized \overline{LTV}_h^2 limits and corresponding first loan LTV_h^1 ratios, using different calibration horizons and an alternative to equation (8) objective function: $ECL_h^2(\overline{LTV}_h^2, LTV_h^1) = ECL_h^H$. Vertical lines denote the averaged \overline{LTV}_h^2 limits with light gray rectangular areas being the 90 percent 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 the 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 the loan’s predicted one-year-ahead PD. For each possible threshold value γ , we compute the pair of accuracy measures:

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

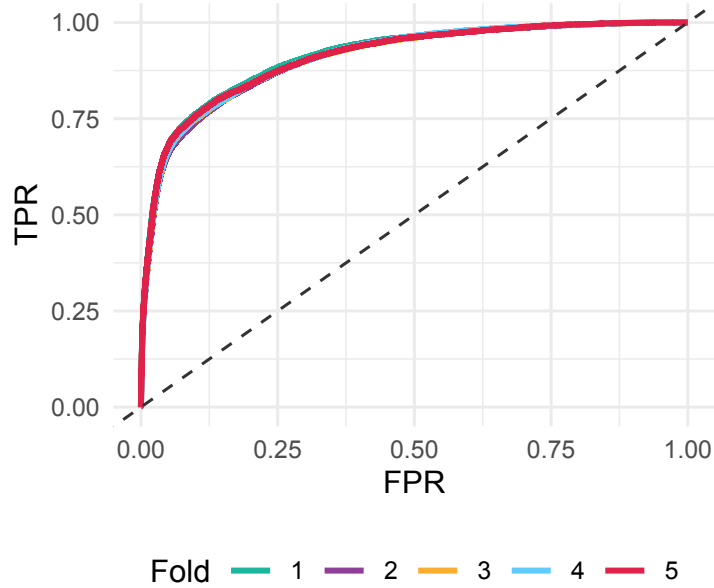
$$\text{FPR}_\gamma := \frac{\text{FP}_\gamma}{\text{N}} = \frac{\text{Number of incorrectly specified “0” cases}}{\text{Total number of “0” cases}} \quad (\text{False positive rate}).$$

The ROC curve is then constructed by plotting the FPR_γ on the x -axis against TPR_γ and 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 summarize 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 the AUROC at which level a classification model is signified as “good,” 70 percent level usually deemed satisfactory.

To avoid overfitting, instead of computing AUROC values in-sample, we assess the model’s discriminatory power by performing five-fold cross-validation. The model is iteratively reestimated on each of the five 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 nonperforming loans well, since the AUROC measure is more than 90 percent. Moreover, little variance in AUROC measures across different folds suggests 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

Note: AUROCs correspond to measures of the model’s discriminatory power, using a five-fold cross-validation procedure.

C Iso-Impact Curves

Assume that new limits on maturity and $\text{oDSTI}^{(*)}$, \bar{M} and $\overline{\text{oDSTI}}^{(*)}$, respectively, are imposed. Since we are only considering policy tightening options, let $\bar{M} \leq 30$, $\overline{\text{oDSTI}} \leq 40$ 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 a mortgage loan at all. Specifically, consider an initial mortgage sample consisting of n individual loan contracts, each characterized by its initial amount D_k , actual oDSTI_k and oDSTI_k^* ratios and maturity at origination M_k , $k = 1, \dots, n$. 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 $\{\overline{\text{oDSTI}}, \overline{\text{oDSTI}}^*, \bar{M}\}$ 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:

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

- 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 that 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. Specifically, no household will take the mortgage if its initial size D_k would reduce more than 10 percent or its DSTI ratio would increase more than 10 p.p. due to the new regulatory framework. Effectively, this implies two new individual limits $\overline{D}_k = 0.9D_k$, $\overline{\text{oDSTI}}_k = \min \{ \text{oDSTI}_k + 10\text{p.p.}, \overline{\text{oDSTI}} \}$.
- If $M_k > \overline{M}$, we assume that the 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 remain 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 the mortgage's initial amount D_k is being reduced to the level $D_{0,k}$ until the 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.



PUBLICATIONS

Micro-Assessment of Macprudential Borrower-Based Measures in Lithuania
Working Paper No. WP/2023/227