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Household Behavior under Macroprudential Borrower-Based Measures

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ABSTRACT: This paper develops a life cycle model to study household choice under macroprudential borrower-based measures (BBMs). The model is extended to multiple heterogeneous households, allowing to assess both aggregate and distributional effects of BBMs on mortgage and housing demand. The framework is applied to Lithuanian and Slovak distributional data to quantify the impact of various BBM configurations. We find that the presence of binding BBMs can usefully dampen mortgage and house price growth. However, tight regulation may also redirect demand towards lower-valued housing, while pushing households into the rental market. In particular, loan-to-value (LTV) limits are most constraining for households with little or no initial wealth. This highlights the distributional consequences of BBMs and the importance of designing regulation to account for borrower characteristics.

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Executive Summary

Quantifying the impact of macroprudential borrower-based measures (BBMs) requires a rigorous framework to analyze borrower behavior under changing conditions. While significant progress has been made in understanding how BBMs contribute to household resilience, models that assess their effects on credit uptake and housing choices remain limited. Existing frameworks are often stylized and lack strong microfoundations.

This paper presents a micro-founded, heterogeneous-agent model designed to quantify the direct effects of BBMs—loan-to-value (LTV), debt-service-to-income (DSTI), debt-to-income (DTI), and maturity limits—on credit and housing decisions at both individual and aggregate levels. The framework is based on a life-cycle model of a resource-constrained household that makes rental, home purchase, and borrowing decisions. The household chooses not only monetary quantities—such as the price of housing and the amount to borrow—but also the duration of renting, saving, and borrowing. The model nests corner cases, including the decision to remain a renter for life or to purchase a home without prior saving or borrowing.

The single-household model is extended to a setting with many heterogeneous households. Although each household solves the same optimization problem, differences in preferences, endowments, and constraints generate variation in optimal decisions. This results in heterogeneity in loan parameter choices, which can be aligned with observed distributions in data over time. The model thus enables construction of relevant counterfactuals for any chosen period.

We apply the model to Lithuania and Slovakia—two European countries with well-established macroprudential BBM frameworks—and estimate it using rich distributional data on mortgage characteristics, including LTV, DSTI, DTI ratios, and loan maturities. Using the estimated models, we conduct a series of counterfactual policy experiments.

For Lithuania, we first show that the adoption of appropriate BBMs during the pre-global-financial-crisis (GFC) buildup of financial imbalances could have restrained credit and house price growth. Second, our counterfactual analysis suggests that, in the absence of BBMs following the GFC, housing demand would have been front-loaded, leading to a substantial increase in both credit demand and house prices. Finally, we examine alternative BBM configurations that could have helped moderate the post-Covid increase in credit and house price imbalances.

In Slovakia, BBMs include various exemptions and speed limits that banks can apply at their discretion. However, delegating such decisions to banks may result in inferior outcomes, as exemptions are not necessarily directed toward sensitive groups, such as young or first-time buyers (FTBs). We show that tight BBM regulation can lead to extended periods of renting, particularly for liquidity-constrained households. Analyzing a streamlined framework with borrower-segment-specific LTV differentiation, we find that it can effectively curb credit and house price growth while maintaining access to finance for FTBs.

1 Introduction

Amid challenges stemming from high household debt, elevated house prices, and economic uncertainty, macroprudential policymakers are increasingly considering the adoption or recalibration of borrower-based measures (BBMs), such as loan-to-value (LTV), debt-service-to-income (DSTI), debt-to-income (DTI), and maturity limits.[1] These measures aim to promote financial stability by enhancing household resilience and by mitigating rapid increases in credit and house prices.[2] While these objectives are paramount, BBMs can also give rise to distributional effects and other unintended consequences, particularly by affecting access to credit and housing across different household groups (Caloia, 2024). As a result, it is essential for regulators to understand the potential impacts of such policies—both prior to their implementation or adjustment, and in the aftermath.

Substantial progress has been made in improving data availability for analyzing the effects of BBMs, with many countries collecting detailed loan-level information. This has advanced the understanding of BBMs' role in strengthening systemic *resilience*. Research shows that consistent use of BBMs can strengthen household resilience, lower credit risk, and thereby enhance the stability of the banking sector (e.g., Kelly and O'Toole, 2018; Nier et al., 2019; Dirma and Karmelavičius, 2025; Gross and Población, 2017; Giannoulakis et al., 2023; Bouis et al., 2025).

However, even with rich datasets, policymakers often lack robust analytical tools to evaluate how changes in BBMs would influence *credit and housing* outcomes. Empirical approaches have traditionally relied on cross-country macroeconomic data (e.g., Lim et al., 2011; Cerutti et al., 2017; Richter et al., 2019; Alam et al., 2025).[3] Although generally insightful—often finding BBMs to impact credit with less certain effects on house prices (see Biljanovska et al., 2023)—these approaches can be impractical for country-specific applications. Recent advances in loan-level analysis have enabled researchers to empirically examine both aggregate and distributional effects of BBMs *ex post* (e.g., Aastveit et al., 2021; Hodula et al., 2023, 2025; Abreu et al., 2024; van Bekkum et al., 2024). However, such studies typically rely on natural experiments triggered by past policy changes, which often involve simultaneous adjustments to multiple BBMs. This complicates causal identification (Grodecka, 2020), limits the generalizability of findings and, being inherently *ex post*, constrains their usefulness for forward-looking policy design.

[1]BBMs have been increasingly adopted across advanced and emerging market economies in the aftermath of the global financial crisis (GFC). According to the IMF's Integrated Macroprudential Policy (iMaPP) Database, as of end-2023, 47 EMs and 32 AEs employed some type of BBMs.

[2]Excessive credit growth often precedes financial crises (Schularick and Taylor, 2012; Claessens and Köse, 2013; Jordà et al., 2013), with households often failing to internalize the externalities their borrowing imposes on others (Bianchi, 2011; Lorenzoni, 2008; Jeanne and Korinek, 2019). Credit-fueled housing booms can be particularly dangerous, as their collapse tends to lead to deep and prolonged recessions (Jordà et al., 2015a,b, 2016) .

[3]These cross-country studies face some limitations. For example, reverse causality is a persistent concern, as BBMs are frequently introduced in response to growing financial vulnerabilities. Moreover, they rely on binary indicators of BBM adoption and do not account for initial conditions, underlying distributions, and non-linear effects.

This paper develops a micro-founded model that enables *ex ante* assessment of household housing and credit choices under alternative macroprudential policy settings. Existing frameworks for *ex ante* policy evaluation are often stylized and lack robust microfoundations (e.g., Reichenbachas, 2020; Kukk and Levenko, 2024), limiting their ability to capture how individual borrowers optimally respond to policy changes. Our framework addresses this gap by modeling heterogeneous households' optimal choices, enabling quantification of policy effects on both individual and aggregate credit and housing demand.

Under the framework, households choose not only how much to save, borrow, and spend on housing over their life cycle, but also *when* to purchase a home—or whether to rent instead—while being subject to three BBMs: LTV, DSTI, and loan maturity limits.[4] The model allows for optimal switching between states of constraint bindingness when regulations or model parameters change, embedding non-linearities and corner solutions. By incorporating heterogeneity in endowments and preferences, the model generates variation across households—not only in loan characteristics but also in the decision whether to borrow or purchase a home in the first place. The resulting mortgage distributions can be matched to their empirical counterparts, allowing to construct counterfactual scenarios over different time periods and for complex policy packages.

We apply the model to Lithuanian distributional data on LTV, DSTI, and loan maturity to simulate the effects of BBMs over the past two decades. We show that, during the pre-GFC credit and housing boom, a timely tightening of BBMs could have curbed credit and house price growth by delaying households' homeownership and reducing the amount of credit demanded, partly through shifts toward lower-quality housing. In the post-GFC period, we find that the counterfactual removal of BBMs would have front-loaded housing demand and led to a marked increase in credit uptake and house prices, highlighting the stabilizing role of BBMs as risk-taking revived. Finally, we show that containing the post-Covid surge in credit and house prices would have required tighter BBMs than those that had been in place, albeit with distributional consequences.

The second country to which we apply the model is Slovakia, which experienced rapid credit and house price growth during the 2010s and responded by introducing BBMs to contain emerging financial imbalances. Unlike Lithuania's relatively uniform approach, Slovakia's BBM framework includes several distinct features—most notably, exemptions and speed limits that banks can apply at their discretion. We adapt the model to reflect these Slovakia-specific

[4]Different BBMs tend to bind under different macroeconomic conditions. For instance, when interest rates are low, mortgage payments—and thus DSTI ratios—typically decline, reducing the effectiveness of DSTI limits. In such environments, DTI limits are more likely to bind. Similarly, LTV limits often become more binding during periods of rising house prices, as they increase the required down payment for new borrowers. See, e.g., De Stefani (2025) for evidence that the sharp rise in interest rates during 2021–23 pushed many potential borrowers above mortgage payment-to-income limits in the US.

elements and calibrate it using Slovak data. Delegating discretion over exemptions to banks, as practiced in Slovakia, may be inferior from both social and risk-based perspectives: while social objectives might favor exemptions for younger or lower-income first-time buyers (FTBs), lenders may instead allocate exemptions toward riskier but more profitable borrowers. Consistent with this concern, we show that tight BBMs can lead to prolonged periods of renting, particularly for liquidity-constrained households, and that a more streamlined regulatory framework with borrower-specific LTV differentiation—aligned with social policy objectives—can still significantly curb credit and house price growth.

While our framework captures household borrowing and housing responses to simultaneous changes in BBMs, it is not designed to assess resilience, equilibrium feedback, or welfare effects. It does not incorporate risk that could lead to default or trigger consumption adjustments, nor does it encompass externalities that would motivate the use of BBMs. Since housing supply is fixed, modeled house value changes reflect demand shifts rather than equilibrium price responses. On the other hand, housing supply is well-known to be inflexible, with housing markets dominated by short- to medium-term demand changes, providing some justification for our approach. In addition, the model abstracts from housing as an investment asset, limiting its ability to capture speculative dynamics. Incorporating these aspects would require alternative frameworks, such as those featuring default risk, stochastic variables, elastic housing supply, or equilibrium feedback. These caveats should be kept in mind when interpreting the results, for we view our framework as focused and complementary to the broader literature that addresses these dimensions.

This paper contributes mainly to two strands of literature. First, our paper contributes to the literature that seeks to construct counterfactuals to assess the impact of BBMs. This strand of research typically relies on loan-level data to generate counterfactual scenarios for both distributional and aggregate outcomes, employing a variety of empirical and simulation methods. For example, Cussen et al. (2015) examine the effect of the 2013–14 LTV limit on loan uptake using Irish data, based on the pre-policy LTV distribution and a probability function that declines exponentially with the gap between preferred LTV and the limit. Applying a similar methodology to Lithuanian data, Reichenbachas (2020) finds that aggregate credit declined for three years after the adoption of the LTV limit. Kelly et al. (2018) simulate credit availability under Irish borrower-based limits and assess its impact on house prices across policy scenarios, finding that LTI limits are more binding than LTV limits, which has been corroborated by Lindner and Albacete (2017) based on Austrian data. Using difference-in-differences approaches and pre-policy-change data, van Bekkum et al. (2024) and Aastveit et al. (2021) find that households in the Netherlands and Norway, respectively, became less leveraged but also hold less liquidity following the implementation of an LTV limit. Similarly, DeFusco et al. (2020) find that the Dodd–Frank *Ability-to-Repay rule* significantly reduced participation in the real estate market and household leverage. Using post-policy data, De Araujo et al. (2020) show that the introduction of an LTV limit in Brazil led households to make larger down payments and purchase more affordable homes. Similarly, Kukk and Levenko (2024) find that the adoption of a DSTI limit in Estonia reduced new housing loan volumes by an average of 10 percent. In contrast to these papers, our model is micro-founded, which has the advantage of modeling optimal household behavior under changing policy measures. Besides the tightening impact, which is generally more predictable, our household optimization model provides a basis for *ex ante* assessment of policy loosenings, which are otherwise difficult to anticipate as borrower responses in terms of debt uptake are uncertain.

Second, it adds to the literature on modeling heterogeneous household choices under macroprudential constraints. Incomplete-market models have been on the forefront of macroeconomics of housing with heterogeneous agents.[5] Recently, such models have been employed to assess the impact of BBMs. In a general-equilibrium framework with default and stochastic house prices, Hatchondo et al. (2015) find that LTV limits reduce default rates but have limited effects on aggregate credit. Nakamura (2023), employing a partial-equilibrium framework with fixed interest rates and house prices, finds that LTV limits cause a larger and more persistent decline in consumption than DTI limits. Gatt (2024), in a general-equilibrium model that abstracts from life-cycle behavior, finds that tighter limits lower homeownership rates, house prices, and overall leverage. To our knowledge, Yao et al. (2015) and Oliveira and Queiró (2023) are the only existing papers that also incorporate multiple BBMs—albeit limited to LTV and payment-to-income constraints— and match household heterogeneity to observed distributions. Using Norwegian data, Yao et al. (2015) show that reducing the LTV limit dampens housing transactions—especially among young households—while modestly boosting consumption and leaving leverage largely unchanged. Oliveira and Queiró (2023), based on Portuguese data, find the LTV cap reduces mortgage debt-to-output and eliminates defaults but lowers household welfare, mainly for income- and wealth-poor agents. In both papers, as in incomplete-markets models more broadly, the source of heterogeneity in their framework differs from that in ours: it stems from idiosyncratic and uninsurable income risk, whereas in our framework, heterogeneity arises from differences in preferences and endowments and there is no idiosyncratic or aggregate uncertainty. Calibration in incomplete-market models is typically limited to the pre-policy-change steady state, and analysis is confined to comparisons between pre- and post-policy-change steady states, potentially including a transition path. In contrast, our approach allows for calibration to

[5]Foundational work in this area has primarily focused on comparing steady states before and after an unexpected policy change (e.g., Gervais, 2002; Chambers et al., 2009; Fernandez-Villaverde and Krueger, 2011). More recent contributions have extended the analysis to examine housing dynamics at business cycle frequency (e.g., Iacoviello and Pavan, 2013; Favilukis et al., 2017; Kaplan et al., 2020). For a comprehensive overview of the macroeconomics of housing, see Piazzesi and Schneider (2016).

both distributional and aggregate data over any period of interest and supports the construction of rich counterfactual scenarios.

The paper is structured as follows. Section 2 presents the model, its basic mechanics, as well as simulation and estimation techniques. Section 3 applies the framework to Lithuanian and Slovak data. Section 4 concludes.

2 Modeling Framework

This section introduces a novel framework for analyzing household behavior under macroprudential BBMs. At its core is a life-cycle model of a resource-constrained household making decisions about renting, purchasing a home, and borrowing. The framework endogenizes duration, allowing the household to choose not only financial variables—such as the house value and the loan amount—but also the timing of key decisions, including how long to rent and save, and how long to borrow. The model accommodates corner solutions, such as the household optimally choosing to rent for life or to purchase a home without prior saving or borrowing.[6]

The single-household model is extended to a framework with multiple heterogeneous households. Although all households face the same underlying decision problem, differences in preferences, endowments, and constraints lead to variation in their optimal choices. This framework enables the analysis of aggregate household behavior and allows for the assessment of the distributional effects of macroprudential BBMs.

2.1 The Household's Problem

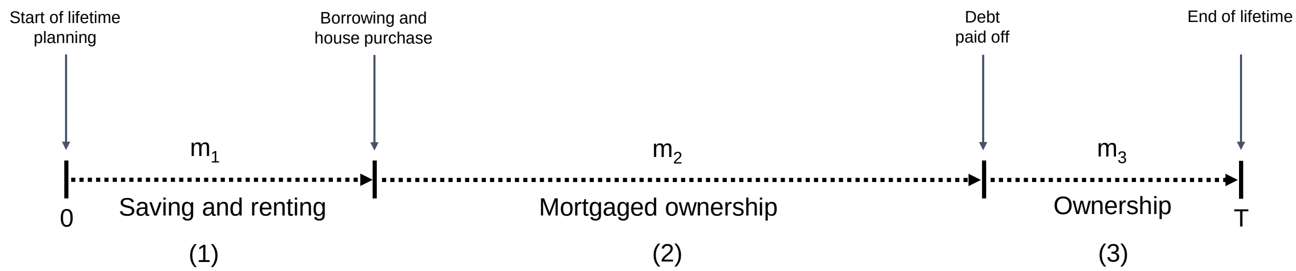
2.1.1 The Life Cycle

We assume a household whose lifetime spans T months and generally consists of three stages or periods: (1) renting while saving for a house purchase, with a duration of m_1 months; (2) homeownership with a mortgage for m_2 months; and (3) ownership without a mortgage for m_3 months. The life cycle is depicted in Figure 1 and explained in more detail below.[7]

[6]For simplicity, we assume that the household does not have any other loans in addition to the housing loan. Therefore, throughout the paper the terms *loan*, *debt*, and *mortgage* are used interchangeably. Likewise, the terms *period*, *stage*, or *phase* of a household's life cycle will be treated as synonyms.

[7]The possibility of selling the house, a reverse mortgage, bequests or other complications are ruled out to keep the framework parsimonious and focused. For tractability, there is no idiosyncratic or aggregate uncertainty, and we assume that household default is not internalized, with consumption needs constraining the relative debt size, in addition to BBM limits.

Figure 1: Household's Life Cycle



Period 1. The household earns income I_1, consumes C_1, and rents a house costing a fraction ρ of the market value of the rental house R, i.e., ρR. The difference between income, consumption, and rent constitutes monthly savings ($I_1 - C_1 - \rho R$) that are reinvested throughout the period, earning an annual interest rate of r_d. It is further assumed that at the beginning of the period, the household receives a lump-sum endowment equal to A_0, which is invested throughout the period, earning an annual return equal to r_A. The value of this investment and the total value of the reinvested monthly savings amount to the down payment for a future house purchase:

$$d = A_0 g(r_A, m_1) + z(r_d, m_1)(I_1 - C_1 - \rho R), \tag{1}$$

where $g(r_A, m_1)$ and $z(r_d, m_1)$ are asset return multipliers:

$$g(r_A, m_1) := \left(1 + \frac{r_A}{12}\right)^{m_1}, \tag{2}$$

$$z(r_d, m_1) := \left[\left(1 + \frac{r_d}{12}\right)^{m_1} - 1\right] \Big/ \frac{r_d}{12}, \tag{3}$$

with limiting case $z(0, m_1) = m_1$.[8]

House purchase. At the end of the period, the household uses the saved down payment d and borrowed funds D to purchase a house valued at V:[9]

$$d + D = V. \tag{4}$$

Period 2. The household earns income I_2, consumes C_2, and lives in the purchased house. The residual amount between income and consumption goes to servicing its debt on a monthly basis:

$$I_2 - C_2 = D \cdot f(i, m_2), \tag{5}$$

[8] $g(r_A, m_1)$ is the total return of a compounded annual interest r_A over m_1 months. $z(r_d, m_1)$ is the total return of a constant stream of monthly income that is reinvested throughout Period 1, with an annual rate of r_d. For simplicity, interest rates are exogenous and not affected by credit risk factors including loan maturity.

[9] The V can be thought of as a function of valuations of housing attributes such as location, size, or number of rooms.

where i is the annual interest rate, m_2 is both the duration of Period 2 and the loan term, and $f(i, m_2)$ is a multiplier that projects loan size (D) into monthly payments, assuming an annuity amortization scheme:

$$f(i, m_2) := \frac{i}{12} \Big/ \left[1 - \left(1 + \frac{i}{12} \right)^{-m_2} \right], \tag{6}$$

with $f(0, m_2) = 1/m_2$.[10]

Debt is paid off. Throughout Period 2, the household has been building equity with monthly loan installments, so the debt is fully paid off at the end of this period.

Period 3. Since all debt is paid off, the household spends all income I_3 on consumption C_3:

$$I_3 = C_3. \tag{7}$$

Naturally, all stages add up to the household's lifetime:

$$m_1 + m_2 + m_3 = T. \tag{8}$$

2.1.2 Borrowing Constraints

The household's debt uptake is subject to three borrowing constraints that are imposed by the lender, or set by a macroprudential authority:

$$\text{LTV limit:} \quad \lambda \geq \frac{D}{V}, \tag{9}$$

$$\text{DSTI limit:} \quad \delta \geq \frac{D \cdot f(i, m_2)}{I_2}, \tag{10}$$

$$\text{Maturity limit:} \quad \mu \geq m_2. \tag{11}$$

The LTV constraint caps the loan amount relative to the value of the collateral (i.e., the house) and, together with the financing equation (4), implies a minimum down payment requirement: $d \geq (1 - \lambda)V$. The DSTI limit restricts the share of income that can be used for monthly debt service—covering interest and principal payments—such that the household cannot allocate more than a fraction δ of its income to debt repayment. The maturity limit imposes an upper bound on the loan term and, since it aligns with the duration of Period 2, also restricts the length of the mortgaged homeownership phase.

[10] Other amortization schedules could be assumed, e.g., linear with average $f(i, m_2) := (24 + i + i \cdot m_2) / (24 \cdot m_2)$.

2.1.3 Preferences

The rational household derives its utility from consumption and the relative value of the house it lives in. We assume an intra-period utility function $U_t(C_t, V_t^H)$ that takes the following form:

$$U_t(C_t, V_t^H) := \log C_t + \theta_t \log\left(V_t^H - a_t\right), \text{with } t \in \{1,2,3\}, \tag{12}$$

where parameter θ_t governs the weight of housing versus consumption and $V_1^H \equiv R$ and $V_2^H = V_3^H \equiv V$.[11] $(V_t^H - a_t)$ is housing quality expressed as the house value V_t^H minus the reservation value a_t, i.e., the minimum acceptable value for a house.

Parameter a_t is introduced for three reasons.[12] First, it provides a nominal anchor for house values and thus ensures that $\left(V_t^H - a_t\right)$ is a signal of quality from which utility is derived.[13] Second, mapping a national house price index to a_t ensures that model-generated house value choices (V_t^H) will generally follow house price dynamics for a given country in our simulations. Third, the use of a_t allows the model to replicate the empirically observed correlation between interest rates and DSTI ratios (see Section 2.2 and Figure 2).[14]

As our model focuses on the demand side and does not explicitly incorporate housing supply, it cannot capture the full impact on house prices, only the one-directional impact on house value choices. In practice, however, housing supply is often inelastic, at least in the short to medium term, implying that shifts in demand will likely translate into price changes. Therefore, our modeled changes in V can be interpreted as price effects driven by demand shifts.

The intra-period utility functions are multiplied by the duration of each period m_t and by its weight β_t (with normalization $\beta_1 = 1$), all amounting to lifetime utility U of the following form:

$$U := m_1 \cdot U_1(C_1, R) + m_2 \cdot \beta_2 \cdot U_2(C_2, V) + m_3 \cdot \beta_3 \cdot U_3\left(C_3, V\right). \tag{13}$$

[11] During Periods 2 and 3, the household lives in the very same house, assumed to be constant in value, whereas the rental home in Period 1 does not need be of the same value as the owned house: $R \lesseqgtr V$.

[12] We generally assume that parameters θ_t and a_t can vary across life stages, to allow a better fit of the model in the empirical application of Section 3.

[13] It is more customary to assume a multiplicative value index (value = quality × reservation value), which would imply that (V_t^H / a_t) would represent utility-relevant quality. However, extensive experimentation revealed that such specification would not imply the desirable positive correlation between interest rates and DSTI ratios. Therefore, we assume an additive value index (value = quality + reservation value), with $(V_t^H - a_t)$ representing housing quality that is used for the utility function.

[14] The impact of interest rates on the DSTI ratio is twofold. On one hand, rising interest rates directly increase the DSTI ratio by definition (see eq. 10). On the other hand, it can decrease the DSTI ratio if the substitution effect is large enough, i.e., the household decides to decrease the loan size ($D \downarrow$) in response to a rising borrowing cost ($i \uparrow$). For example, in case of non-binding LTV and DSTI constraints, increasing interest rates will always reduce C_2 and thereby raise the DSTI ratio if the reservation value $a_{1,2}$ is large enough: $\rho z(r_d, m_1) a_1 + a_2 > A_0 g(r_A, m_1) + z(r_d, m_1) I_1$ (see eq. 5 and Appendix A eq. A.26). Simply put, if housing is very important for the household, hence high reservation value ($a_{1,2} \uparrow$), the interest rate will do little to reduce debt size, and thus will translate into higher DSTI ratios.

Weights β_2 and β_3 represent the relative importance of each life stage, or how important (mortgaged) homeownership is compared to renting. Within a given period, all quantities are assumed to be constant and each month is valued equally, e.g., there is no intra-period discounting.

2.1.4 Planning and Solution

The household plans its lifetime before its beginning, internalizing all constraints (1)-(12) and aiming to maximize lifetime utility (13). The model parameters, the length of the household's lifetime T, the endowment A_0, income I_t, returns r_A, r_d, and i, as well as borrowing limits λ, δ, and μ, are assumed to be exogenously given and known with perfect foresight, or in expectation. The control variables are contained in the following vector: $X := (C_1, C_2, C_3, d, D, R, V, m_1, m_2, m_3)$, which also include the lengths of each life stage. The can be formulated as the following compact optimization problem:

$$U = m_1 \cdot U_1(C_1, R) + m_2 \cdot \beta_2 \cdot U_2(C_2, V) + (T - m_1 - m_2) \cdot \beta_3 \cdot U_3\left(I_3, V\right) \longrightarrow \max_{\{C_1, C_2, R, V, m_1, m_2\}}$$

s.t.

$$V = A_0 g(r_A, m_1) + z(r_d, m_1)(I_1 - C_1 - \rho R) + \frac{I_2 - C_2}{f(i, m_2)},$$

$$\lambda \geq \frac{I_2 - C_2}{V f(i, m_2)}, \qquad \delta \geq \frac{I_2 - C_2}{I_2}, \qquad \mu \geq m_2.$$

The household problem is solved using the Kuhn-Tucker optimization technique, which is well suited for handling inequality constraints. Solution details are provided in Appendix A. Given that the first-order conditions (A.1)-(A.16) are highly non-linear and involve multiple inequality constraints, the model solution combines numerical and analytical approaches, implemented using `R`. The result is a vector of optimal controls:

$$X^* = X^*(\Lambda, \Theta) = \underset{X \in \mathcal{X}_\Lambda}{\arg\max}\, U\left(X|\Theta\right), \tag{14}$$

with borrowing limits $\Lambda := (\lambda, \delta, \mu)$, the constrained decision space $\mathcal{X}_\Lambda$, and parameters $\Theta := (\theta_t, a_t, T, \beta_t, \;\; A_0, \rho, I_t, r_A, r_d, i), \forall t \in \{1, 2, 3\}$ with $\beta_1 = 1$.

We define some additional quantities that will be of interest in the analysis of macroprudential BBMs and their effects:

$$\text{LTV} := \frac{D}{V} \cdot 100\%, \qquad \text{DSTI} := \frac{D \cdot f(i, m_2)}{I_2} \cdot 100\%, \qquad \text{Maturity} := \frac{m_2}{12},$$

$$\text{DTI} := \frac{D}{12 \cdot I_2}, \qquad \text{PTI} := \frac{V}{12 \cdot I_2}, \qquad \text{dTI} := \frac{d}{12 \cdot I_2}.$$

The latter three are the debt-to-income (DTI), price-to-income (PTI), and down payment-to-income (dTI) ratios, respectively.

2.2 Basic Mechanics

Having specified the model, we illustrate its solution for a single household and highlight some basic mechanics by carrying out a sensitivity analysis. For example, we assume that the household has no initial assets, expects to live for 40 years, earning a monthly income stream of 2,000, and seeking to live in a house that would be valued at more than 57,000 (Table 1). The return on investments is 1% and the loan rate is 5%. The household expects its borrowing to be constrained by an LTV cap of 95%, a DSTI limit of 40%, and a maturity limit of 30 years.

Table 1: Illustrative Parameters

λ	δ	μ	θ_t	a_t	T	β_t	A_0	ρ	I_t	$r_{d,A}$	i
0.95	0.4	30·12	0.5	57,000	40·12	1	0	0.0325	2,000	0.01	0.05

Baseline solution. Using the methods described in Appendix A, we solve the household's problem and tabulate the solution in Table 2(a). The household optimally plans to split its lifetime into three stages: (1) 4 years of saving while living in a rental house and accumulating a down payment of 5,339, which will be used to buy a house that costs 106,770; (2) 20 years of mortgaged homeownership, financing the difference between the house price and the down payment with a loan of 101,432 that will be fully amortized by the end of this period; and (3) 16 years of homeownership without the mortgage until the end of the household's lifetime. Such choices would result in an LTV ratio of 95%—exactly at the limit—and a DSTI ratio of 34% – below the respective 40% cap.

Sensitivity to interest rate. Suppose the mortgage lending rate drops from 5% to 2%. The household re-optimizes its life plan, with the updated choices tabulated in Table 2(b). While life stage durations remain unchanged, the value of the purchased house and loan size both increase by around 10%. The bigger loan is accompanied by a 10% higher down payment, keeping the LTV constraint binding at 95%. Although the size of debt is now higher, the resulting DSTI ratio is lower, equaling 28%—the decrease in interest payments is greater than the increase in loan installments ($i \downarrow \implies D \uparrow \cdot f(i, m_2) \downarrow\downarrow$).[14]

In general, the impact of lending rates is non-linear and depends on other model parameters, including borrowing limits. Figure 2 depicts the relationship between the interest rate and key mortgage characteristics, depending on the assumed combination of LTV and DSTI constraints.

Table 2: A Household's Optimal Choice

(a) Baseline solution

m_1	m_2	m_3	V	d	D	LTV	DSTI
4	20	16	106,770	5,339	101,432	95	34

(b) The interest rate (i) drops to 2%

m_1	m_2	m_3	V	d	D	LTV	DSTI
4	20	16	118,059	5,903	112,156	95	28

(c_1) Either the LTV limit (λ) is tightened to 85%

m_1	m_2	m_3	V	d	D	LTV	DSTI
8	15	17	79,776	11,966	67,809	85	22

(c_2) Or the LTV limit (λ) is relaxed to 100%

m_1	m_2	m_3	V	d	D	LTV	DSTI
0	30	10	216,439	0	216,439	100	40

Notes: Life stage durations (m_1, m_2, m_3) are expressed in years. Durations grid ∇^m is generated using step sizes $\Delta^{m_1} = 6$ and $\Delta^{m_2} = 60$.

Under the assumed parametrization, an increase in the interest rate will mostly translate into a higher DSTI ratio.[15] The response of maturity varies: in some cases, the household will decrease loan maturity to reduce the amount of interest paid over its lifetime; in others, the household will increase the maturity in order to lower monthly installments, thereby compensating for the rising interest burden, e.g., to keep the DSTI ratio stable.

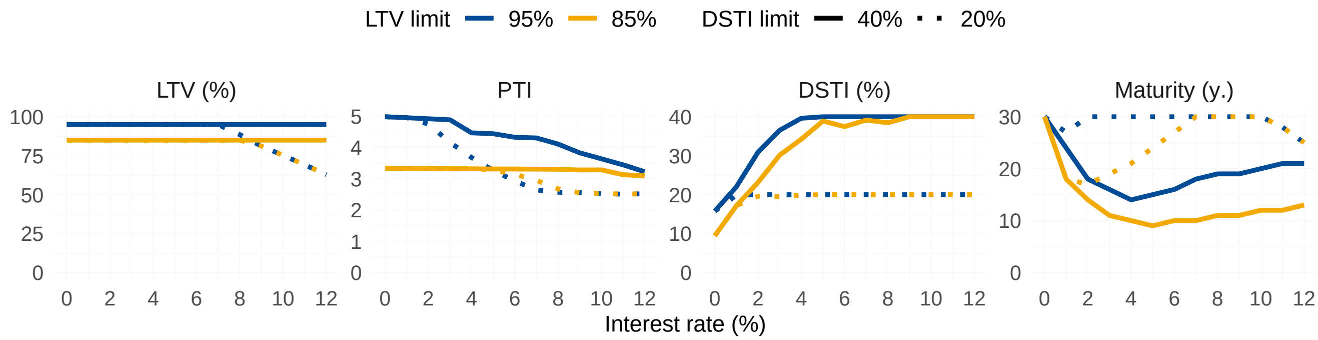
In our baseline example, interest rates do not affect the LTV ratio much. In case of a stringent DSTI limit of 20%, the LTV ratio starts decreasing along with sufficiently high interest rates. Here, two effects reinforce each other: (1) as the interest rate goes up, loan size decreases due to the classic substitution effect; (2) the household reduces the loan size even more, in order to be compliant with the DSTI limit, which becomes increasingly binding due to the increasing rate.

Sensitivity to LTV limit. Suppose a macroprudential authority views the LTV $\leq$ 95% lending practice as unsound, and thus decides to tighten to 85%. One could intuitively expect that the household would use the same down payment of 5,903 to purchase a smaller home, using a 20:3 leverage instead of 20:1. However, such a choice would result in a house value of 39,353, which is significantly below the reservation value, and therefore is strongly suboptimal.

Instead, our modeled household adapts to this regulation by evaluating different options and durations of each life stage, thereby re-optimizing its choices (see Table 2c_1). Interestingly, the saving-renting duration doubles, enabling the household to accumulate a larger down

[15]However, as highlighted by the oscillating solid yellow DSTI line of Figure 2, sometimes the substitution effect can dominate, e.g., under a sufficiently high interest rate, depending on maturity and other parameters (see footnote 14).

Figure 2: Interest Rate Impact on Mortgage Characteristics



Notes: The interest rate is changed unilaterally ($i \in [0\%, 12\%]$, x-axis) using a combination of different borrowing limits ($\lambda \in \{85\% -$ yellow line, $95\% -$ navy line$\}$ and $\delta \in \{20\% -$ dotted line, $40\% -$ solid$\}$), while keeping other parameters at constant values found in Table 1. y-axes represent values of the actually chosen loan parameters. Durations grid ∇^m uses step sizes $\Delta^{m_1} = 6$ and $\Delta^{m_2} = 12$.

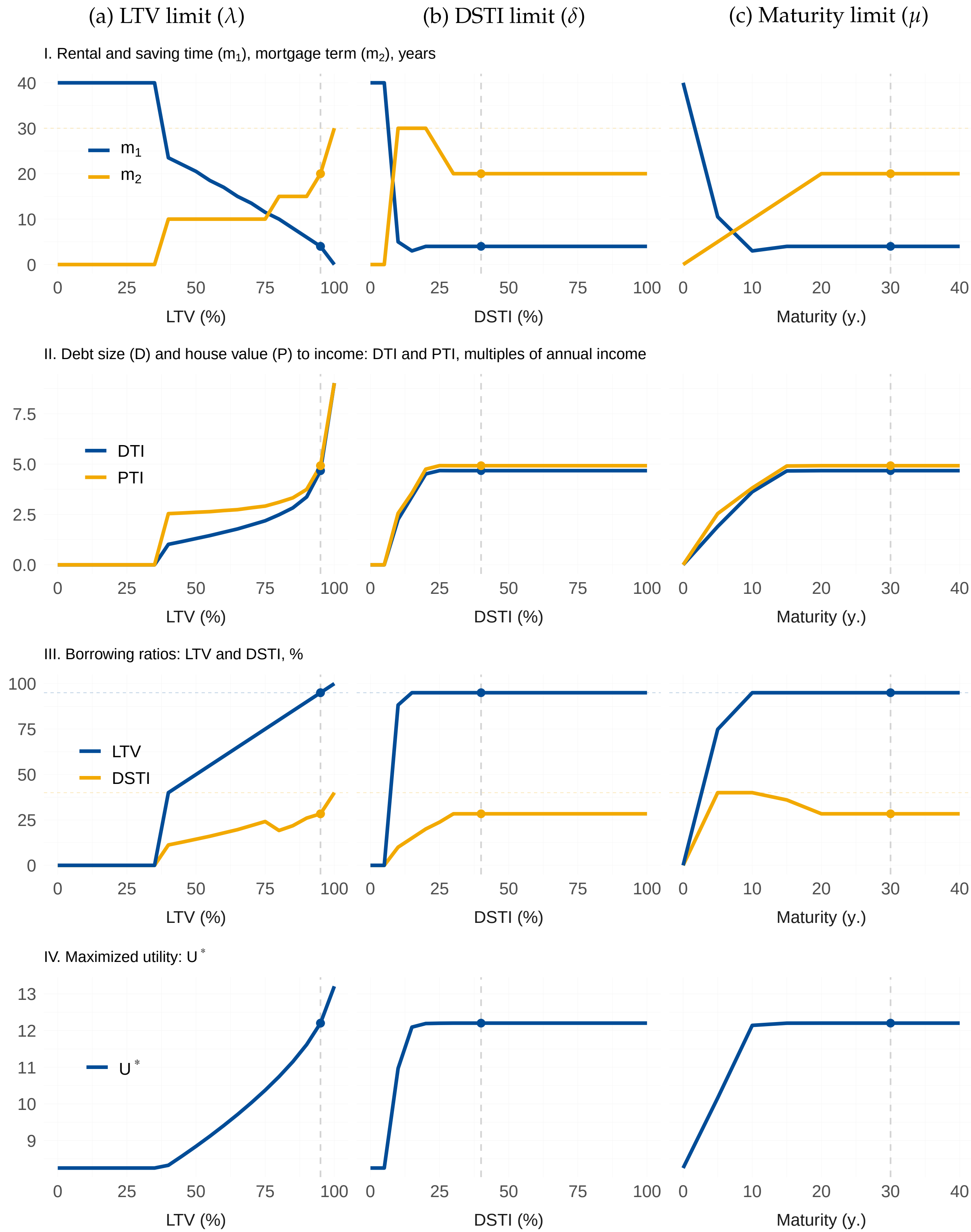
payment, but at the cost of delaying the house purchase for another 4 years. Despite the increase in the down payment, the price of the purchased home and loan size drop by 32% and 40% respectively—a significant decline. Unsurprisingly, the LTV ratio is adjusted downwards to the new 85% limit. Although the loan term decreased from 20 to 15 years, the DSTI ratio fell to 22%, which suggests that the reduced loan size effect dominates. At the same time, the maturity of the loan decreased because the principal became relatively small and the household has additional capacity, in terms of income, to service debt payments.

Suppose, on the other hand, the LTV limit is relaxed from 95% to 100%. Assessing the impact of such relaxation would be difficult without a model, as it is unclear how the borrower would react to an effective abolition of the down payment requirement ($\lambda = 1 \implies d \geq 0$; eqs. 4 and 9). The resulting choices from model re-optimization are tabulated in row c_2 of Table 2. Given that the down payment is no longer needed, the household chooses to borrow and purchase a house immediately, without any saving and renting. The borrower maximizes its leverage by extending the loan term to the 30-year limit and increasing the DSTI ratio to the 40% cap, with the house value equaling the loan size (216,439) and LTV at 100%. In effect, the decision to loosen the LTV constraint is significant, as a mere 5 percentage point (p.p.) relaxation not only doubles housing and mortgage demand but front-loads it by 4 years.

More generally, to illustrate how the model responds to different BBM parameterizations, we conduct experiments similar to those described above by varying each borrowing limit individually. Specifically, LTV and DSTI limits are each set from 0% to 100%, using 5 p.p. increments, whereas the maturity limit is changed from 0 to 40 years, using 5-year increments. The resulting key characteristics are depicted in Figure 3, with the yellow and navy markers representing the initial situation—an LTV limit of 95% and an interest rate of 2% (Table 2b).

Maintaining our focus on the LTV constraint, whose impact is depicted in column (a) of Figure 3, we see that a continued tightening of the limit from 95% to 0% would non-linearly reduce both the loan size and the purchased house value, while increasing the saving-renting

Figure 3: Borrowing Limit Impact on a Household's Choices



Notes: Each column (a-b-c) of subplots refers to a simulation, in which a single borrowing limit (λ-δ-μ) is changed unilaterally (x-axis), while keeping other parameters and limits constant. Each row (I-II-III-IV) of subplots represents a set of optimal choice variables (y-axis) that result from changing borrowing limits. The yellow and navy points mark the initial situation with $\lambda = 0.95$ and $i = 0.02$ (Table 2b). The dashed vertical and horizontal lines refer to the baseline borrowing limits ($\lambda = 0.95, \delta = 0.4, \mu = 360$). Durations grid ∇^m step sizes: $\Delta^{m_1} = 6$ and $\Delta^{m_2} = 60$.

time. Loan maturity as well as the LTV and DSTI ratios would generally decline along with the reduced debt burden.[16] Interestingly, when the LTV limit falls below 40%, the household's borrowing drops to zero, and the rental time jumps to 40 years—it is not worth for the household to borrow, so they choose to permanently live in a rental home. This indicates the model's capacity to embed non-linearities and corner cases. As discussed, LTV loosening to 100% would substantially increase leverage and housing demand, and eliminate saving-renting time.

Note that the maximized utility (U^*, row IV of Figure 3) is non-decreasing with the LTV, and each other borrowing limit. Its curvature reflects the shadow value of each constraint: a flat U^* implies the limit is non-binding, while an upward slope indicates utility gains from loosening.

Sensitivity to DSTI cap. Figure 3 column (b) depicts the impact of changing the DSTI cap. To start from our initial parametrization, a loosening of the DSTI constraint will not affect the household's behavior, as it is not bounded by the 40% limit. Similarly, since the household's optimal DSTI choice is 28%, a slight tightening has no effect. Only when the DSTI limit is reduced to 25% or lower does the household begin to adjust its behavior—reducing debt uptake and house value, while extending loan maturity to stay within the constraint.

Under the baseline parametrization and $i = 0.02$, the DSTI limit has to be at least 10% for the household to start borrowing, otherwise there would be no debt and the household would be a renter for life.

Sensitivity to maturity limit. Figure 3(c) visualizes the impact of the maturity limit. As with the DSTI cap, neither loosening nor a slight reduction of the maturity limit has any effect, as the analyzed household is not bounded by the limit. However, if the maturity limit is tightened below the 20-year mark, the household's debt uptake and house value generally decrease—the household cannot afford high loan installments.

2.3 Simulation and Estimation

While previously we illustrated the model's solution to a single household's problem, this subsection showcases our framework's applicability to multiple heterogeneous households, allowing to assess aggregate and distributional consequences of policy changes. The model and its solution present a demand-side view of the credit and housing market. All subsequent analyses look at first-order direct impacts on household behavior, abstracting from equilibrium and externality effects.

[16] There is a kink in the DSTI's response around the 75% LTV limit, resulting from the household significantly changing the maturity, while the DTI changes only gradually.

2.3.1 Multiple Heterogeneous Households

In our model, a household's endogenous choices X^* are determined by an exogenous combination of preferences, endowments, and interest rates, all represented by a vector Θ, and borrowing limits, vector Λ (eq. 14). If we present a different household with a different set of $\{\Lambda, \Theta\}$ values, we will observe different outcomes. This will be our principle for simulating multiple heterogeneous households and evaluating their optimal choices.

Suppose that there was a household h, characterized by an h-specific pair $\{\Lambda_h, \Theta_h\}$. Adding the subscript $_h$ to equation (14) would result in the following solution for this household's problem:

$$X_h^* = X^*(\Lambda_h, \Theta_h) = \underset{X_h \in \mathcal{X}_{\Lambda_h}}{\arg\max}\, U\left(X_h | \Theta_h\right). \tag{15}$$

To introduce heterogeneity, we assume that Θ_h is an identically distributed random vector:

$$\Theta_h \sim B(\Xi | Z_t), \tag{16}$$

where $B(\cdot)$ is a parametric distribution function with hyperparameter Ξ and conditioned on Z_t—a time series vector of exogenous macroeconomic variables.

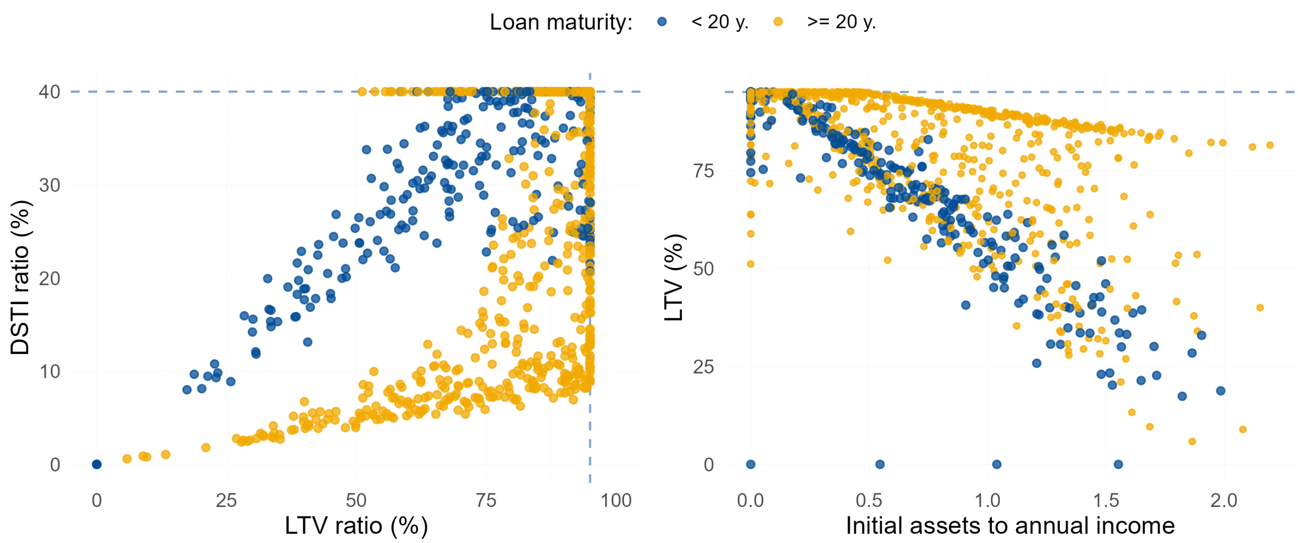
Simulation and aggregation. A number N of households is simulated from the $\Theta_h \sim B(\Xi|Z_t)$ distribution in every quarter t, with $h \in [1, N] \subset \mathbb{N}$. For simplicity, households do not overlap across simulations: each cohort expires at the end of a simulation and is replaced by a new cohort. Optimization problems for each household are solved separately, resulting in an optimal $X_{h,t}^*$ including the LTV, DSTI, and DTI ratios as well as individual choices of loan maturity which are aggregated into quantiles denoted $q(X_t^*|\Lambda_t; \Xi, Z_t)$ using a quantile aggregator function $q()$. The time series vector Z_t is used to generate exogenous dynamics for our model and thus governs the averages of household income, initial assets, interest rates, rental rates, and house prices. The mapping $B\colon \Xi|Z_t \mapsto \Theta_h$ is described in Appendix A.5. For now, we will assume that borrowing limits Λ are identical across all households, but this assumption will be relaxed in Section 3.

Illustration. To illustrate how the model applies to multiple households, 1,000 households are randomly drawn from the $B(\cdot)$ distribution, using hyperparameter Ξ values of Table A.8, and uniformly assuming the following BBMs: LTV $\leq 95\%$, DSTI $\leq 40\%$, Maturity $\leq 30y$.[17] Each simulated household's problem is solved, with the resulting optimal choices plotted in Figure 4.

The resulting scattergrams show that households with heterogeneous preferences will make different choices, even when presented with the same BBMs. The LTV/DSTI points indicate

[17] The hyperparameter estimate $\hat{\Xi}$ is based on Lithuanian data (see Section 3). The resulting parameter Θ_h distributions are depicted in Figure A.18 of Appendix A.5.

Figure 4: Illustration of Simulated Households' Optimal Choices



Notes: 1,000 household simulations using $\hat{\Xi}$ from Table A.8, and $\Lambda_h = \Lambda = \{\lambda = 0.95, \delta = 0.4, \mu = 12 \cdot 30\}$ marked by the the dashed lines. Initial assets to annual income defined as $A_0/(12 \cdot I_1)$. Durations grid ∇^m step sizes: $\Delta^{m_1} = 6$ and $\Delta^{m_2} = 60$.

that some households are bounded by the LTV limit, some by the DSTI, and others by neither of the two limits. The left chart displays a generally positive correlation between the chosen LTVs and DSTIs, corresponding to the debt size that determines both ratio numerators. This indicates that a single BBM, either an LTV or a DSTI, in principle could limit overall credit uptake. However, the slope of the LTV-DSTI relationship is heavily influenced by the chosen maturity, with long-tenured ($\geq 20y.$) loan DSTIs being less reactive to loan size. This means that an extension of loan maturity can reduce the DSTI while keeping the LTV stable, pointing to complementarity benefits of the measures. The right-hand side chart indicates that household initial assets is an important determinant of the LTV ratio. Therefore, the LTV limit can be more restrictive for liquidity-constrained buyers, as will be further discussed in Section 3.2.

2.3.2 Estimation

To be able to use the model for policy purposes, e.g., to examine the impact of macroprudential BBMs on household behavior, the model needs to be brought to the data, so that it is able to reproduce the distributional features of mortgage lending. This would enable us to treat the model-generated quantities as if they were representations of true market conditions, and thereby conduct counterfactual experiments.

To this end, we assume that some distributional characteristics $q(X_t)$ of mortgage lending are observed at time t, including quantiles of LTV, DSTI, DTI, and maturity distributions. The model-generated counterparts $q(X_t^* | \Lambda_t; \Xi, Z_t)$ result from equation (15) solution aggregated over all households using an quantile aggregator function $q()$.

Assuming that we observe borrowing limits Λ_t and macroeconomic data in Z_t, we can estimate household heterogeneity represented by hyperparameter Ξ, such that the squared difference between the observed and model-simulated characteristics is minimized:

$$\{q(X_t) - q\left(X_t^*|\Lambda_t; \Xi, Z_t\right)\}^2 \xrightarrow{\Xi} \min .$$

This is a version of the simulated method of quantiles (SMQ), where we use time series exogenous variables in Z_t and Λ_t, then choose a version of hyperparameter Ξ_0, and simulate the quantiles. In practice, we generate a large grid ∇^{Ξ} of random Ξ values and search for the distance-minimizing solution:

$$\hat{\Xi} := \underset{\Xi \in \nabla^{\Xi}}{\arg\min} \{q(X_t) - q\left(X_t^*|\Lambda_t; \Xi, Z_t\right)\}^2. \tag{17}$$

The estimation procedure will be used in our empirical application of Section 3.

To summarize, this section developed a household decision framework, which could be used to assess the impact of macroprudential BBMs. Since our framework features multiple heterogeneous households making house purchase and rental choices, also endogenizing duration, we can use this framework to investigate distributional effects of policy measures.

3 Applications

We apply our modeling framework to two countries—Lithuania and Slovakia, both of which have been active users of BBMs. Before adopting their respective regulations, each of the two countries experienced a credit and asset price boom that was veiled by financial deepening. These booms ultimately ended in busts, which played a role in motivating the adoption of BBMs and other macroprudential policies.

Despite having implemented these measures for several years, both countries experienced a post-pandemic surge in mortgage lending and house prices. This reflected not only persistent supply constraints—exacerbated by lockdowns and soaring material costs—but also strong demand. This apparent disconnect raises questions about the effectiveness of BBMs in curbing credit and housing demand—questions we investigate using our modeling framework across a range of policy calibrations.

The BBM frameworks in both countries include limits on LTV, DSTI or DTI ratios, and loan maturities, making them well-suited for our analysis. To evaluate these policies, we tailor and estimate the model separately for each country, using distributional data on mortgage characteristics for new lending, along with macroeconomic time series data.

3.1 Case Study: Lithuania

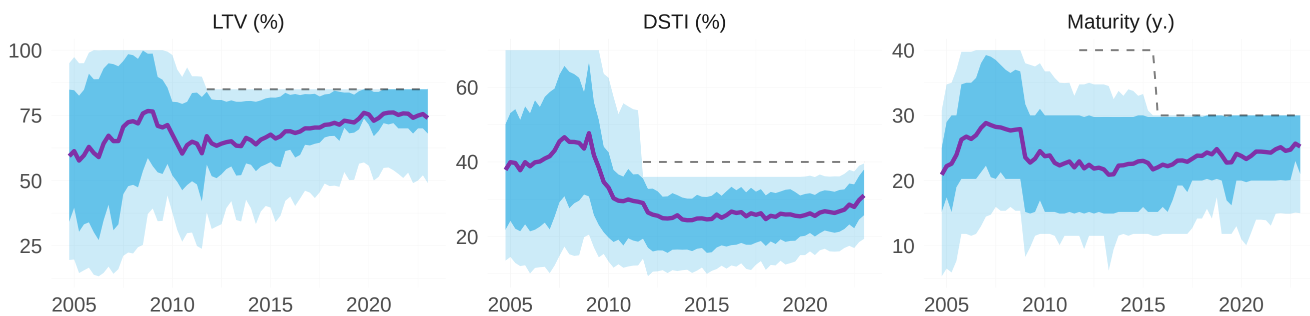
3.1.1 Background

We focus attention to three distinct periods in Lithuania's macrofinancial history.[18]

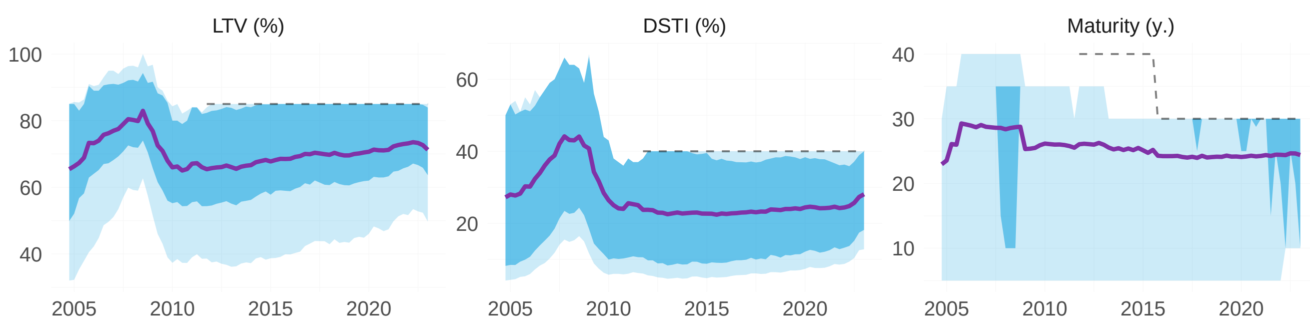
I. 2006-07 — No regulation. In the absence of BBMs or other forms of macroprudential regulation, this period was marked by elevated housing and credit demand, alongside intense competition and increased risk-taking by lenders. Lending standards deteriorated significantly: LTV ratios reached 100% for a quarter of borrowers, implying minimal or no down payments (see Figure 5a). DSTI ratios frequently exceeded 60%, with mortgagors allocating almost two-thirds of their income to debt service. Loan maturities also extended as far as 40 years.

Figure 5: Distributions for New Mortgage Lending in Lithuania

(a) Actual series



(b) Model-simulated series



(c) Model fit (Root Mean Squared Error, RMSE)

	I. 2006-07			II. 2011-20			III. 2021-23		
Percentile	Median	75th	90th	Median	75th	90th	Median	75th	90th
LTV (p.p.)	11.6	2.0	7.5	3.9	2.1	0.0	1.8	0.1	0.0
DSTI (p.p.)	6.6	1.4	13.6	1.1	6.7	3.9	2.8	3.6	2.8
Maturity (y.)	5.8	1.7	0.3	6.3	0.1	0.8	1.7	0.0	0.0

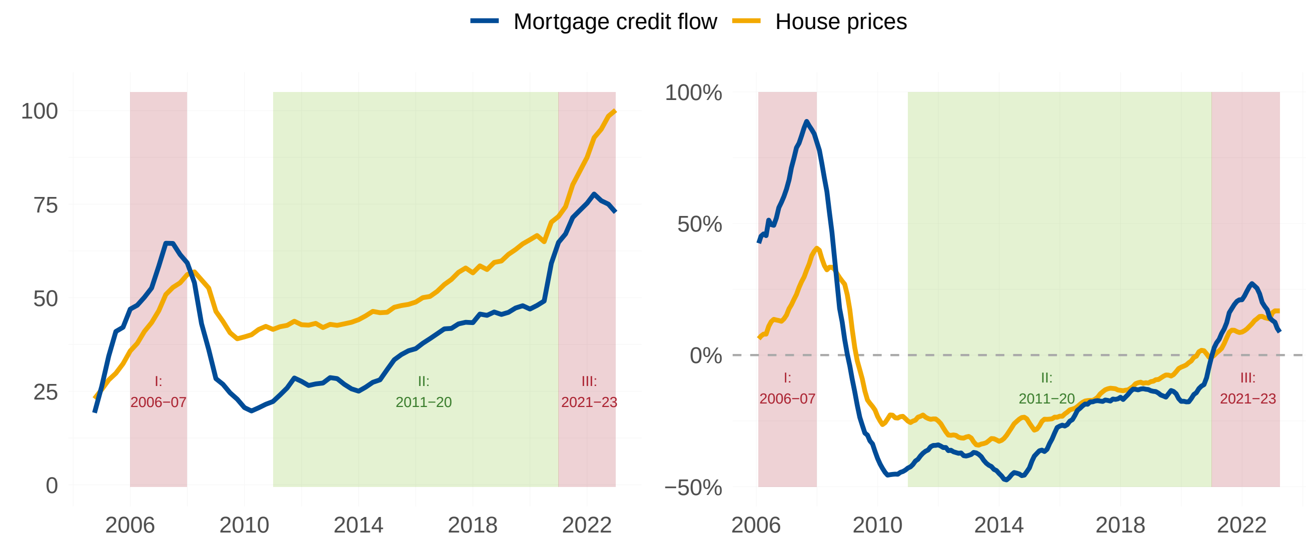
Notes: Purple lines mark averages, the shaded areas – 25th-75th and 10th-90th percentiles, and dashed lines – regulatory BBM limits. The simulated series in (b) are based on Z_t time series of Figure 7, Λ_t limits of Figure 8 and Table 4, and hyperparameter $\hat{\Xi}$ estimates of Table A.8. We assume 10,000 household simulations per each quarter, with $\Delta^{m_1} = 60$ and $\Delta^{m_2} = 60$.

[18] For a more detailed discussion on Lithuania's macrofinancial history, please see Karmelavičius et al. (2022), Karmelavičius et al. (2023), or Dirma and Karmelavičius (2025), and references therein.

Based on Karmelavičius et al. (2022), mortgage issuance exceeded sustainable levels by 66%, while house prices were, on average, overvalued by 20% (see Figure 6). By late 2007, these misalignments had peaked at 88% and 40%, respectively, before collapsing and intensifying the 2008–09 crisis, during which real GDP contracted cumulatively by approximately 17%.

Figure 6: Mortgage Credit and House Prices in Lithuania

(a) Indexed levels (b) Misalignments: overflow and overvaluation



(c) Growth rates and misalignments–gaps

(%)	I. 2006-07 Growth	I. 2006-07 Gap	II. 2011-20 Growth	II. 2011-20 Gap	III. 2021-23 Growth	III. 2021-23 Gap
Mortgage credit flow	49	66	9	-27	23	16
House prices	38	20	5	-19	18	10

Notes: (a) Quarterly flow of new housing loans and repeated-sales house price index, both seasonally adjusted using *loess*. Period III. includes data through to 2023Q1. (b) Measures of misalignments are percent deviations from fundamental values, based on the two-market disequilibrium model of Karmelavičius et al. (2022). (c) Growth rates are average y-o-y growth rates, and gaps are misalignment averages.

II. 2011-20 — Adoption of BBMs. Following the GFC, Lithuania was one of the early adopters of BBMs, introducing its framework in 2011, and revising it in 2015. An LTV limit of 85%, a DSTI cap of 40%, and a maturity limit of initially 40 years, and later revised down to 30 years, were set (see Table 3). As risk-taking had receded and lending standards improved, the regulations were not distortionary upon their inception.

The post-crisis period was initially relatively tranquil, but following Lithuania's adoption of the euro in 2015, its credit and housing markets picked up, with credit and house prices growing on average by 9% and 5%, respectively. As shown in Figure 5a, BBMs helped prevent a deterioration in lending standards, containing increases in LTVs, DSTIs, and loan maturities.

III. 2021-23 — Pandemic spurt. Contrary to initial expectations, the pandemic period saw a spurt in housing demand, partly financed by an increasing volume of credit. Amid lagging

Table 3: Headline BBM Limits in Lithuania

	LTV	DSTI	Maturity^{o}	Maturity
Limit	85%	40%	40 years	30 years
Applicable since	2011	2011	2011	2015

Note: The 40 y. maturity^{o} limit was in force until 2015 when the limit was revised down to 30 y.

housing supply, gaps in credit and house prices opened up, averaging 16% and 10% respectively, and peaking at 27% and 17% (Karmelavičius et al., 2022, and Figure 6c). With house prices rising faster than down payments, leverage increased, as reflected in slightly higher DSTI ratios and loan maturities.

Having described those periods, three natural questions arise about the impact of BBMs on credit and housing dynamics in the context of Lithuania. First, what would have happened to household credit uptake and housing demand had the authorities adopted BBM regulation prior to the GFC? Second, have BBM limits dampened credit and housing demand since their adoption? Third, what other parametrizations could have alleviated the 2021-23 spurt? We seek to showcase our modeling framework by addressing these questions.

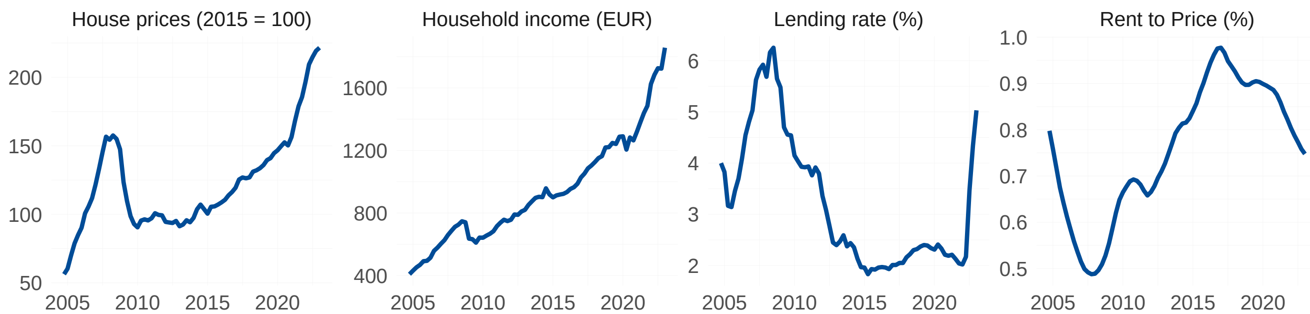
3.1.2 Bringing the Model to the Data

Application of the modeling framework to Lithuania is straightforward, as the country has a standard three-instrument BBM toolkit, for which our model is designed.[19] However, to analyze policies, we need to estimate model hyperparameters Ξ by matching the simulations to observed data. To this end, we use the distributional characteristics of new mortgage contracts from historical time series as our target variable $q(X_t)$, specifically the quantiles of LTVs, DSTIs, and loan maturities, as shown in Figure 5(a). To generate model dynamics, a set of exogenous macroeconomic series Z_t is used, including a house price index, household disposable income, mortgage lending rates, and rent-to-price ratios, as shown in Figure 7.

Next, we describe how the borrowing constraint vector Λ_t is constructed. Our dataset spans the period from 2005Q1 to 2023Q1, covering both phases with and without macroprudential BBMs. For periods when regulation was in effect, we parametrize the borrowing constraints using the values reported in Table 3. For the pre-regulatory period, up to 2011, we assume the

[19] Besides headline limits, Lithuania adopted two additional DSTI measures as of 2015: (1) a stressed DSTI$^{*} \leq 50\%$ limit, which assumes a 5% interest rate; and (2) an exemption, allowing credit institutions to apply a DSTI $\leq 60\%$ cap for creditworthy customers, up to 5% of the institution's mortgage issuance. Also, an LTV^{2} cap for secondary mortgages was adopted since 2022 (see Dirma and Karmelavičius, 2025). The model version that we use does not include any of these additional measures, as they affected only a tiny share of our sample.

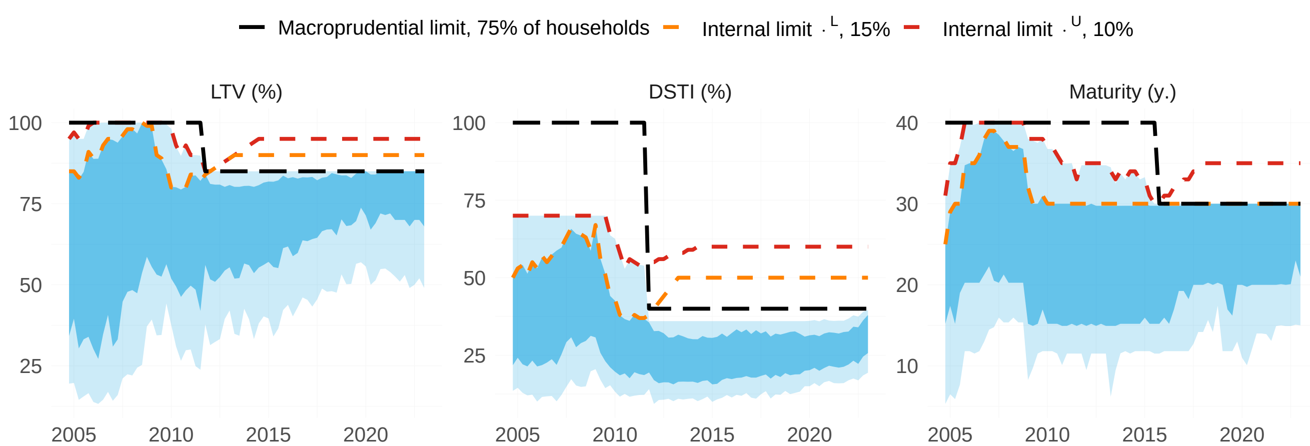
Figure 7: Exogenous Time Series Data for Lithuania



presence of implicit BBMs by capping LTV and DSTI ratios at 100%, and loan maturity at 40 years.

In addition to BBMs, we assume that lenders impose their own standards, hereafter referred to as internal limits.[20] While these internal limits are unobservable, we do observe the realized mortgage outcomes. For the first part of the sample, up to 2011 when BBMs were not yet in place, we approximate internal limits using the upper percentiles of the LTV, DSTI, and maturity distributions—represented by the yellow and orange lines in Figure 8. For the second part, when BBMs were active, we assume internal limits to be more lenient than the regulatory caps, broadly resembling the lending conditions of the pre-GFC period and capturing the idea that crisis memory dissipates as lenders are eager to take on more risk.

Figure 8: Macroprudential BBMs and the Assumed Internal Limits in Lithuania



Notes: The shaded areas represent the 25th-75th and the 10th-90th percentiles of actual mortgage issuance, taken from Figure 5(a). Macroprudential limits are the headline BBMs since their adoption in 2011, and before that—LTV $\leq$ 100%, DSTI $\leq$ 100%, and Maturity $\leq$ 40 y. Internal limits coincide with the 75th and the 90th percentiles until 2011, and are assumed to be higher than macroprudential caps afterwards.

Since a mix of macroprudential BBM caps and internal limits is assumed, it is necessary to determine the effective borrowing limit applied to each household in the simulations. We assume that each household h is subject to the macroprudential limit, but may also face an internal limit

[20] We introduce internal limits for two reasons: first, to improve the model fit; and second, to yield plausible results in counterfactual analyses, particularly in scenarios involving policy relaxation – by accounting for supply-side constraints on risk-taking.

with some probability. The full scheme is summarized in Table 4, where $(\cdot)^L$ denotes the lower internal limit and $(\cdot)^U$ the upper limit.

Table 4: Household *h*-Specific Borrowing Limits

Probability		75%	15%	10%
	$\lambda_h =$	λ	$\min\left\{\lambda^L, \lambda\right\}$	$\min\left\{\lambda^U, \lambda\right\}$
Limit	$\delta_h =$	δ	$\min\left\{\delta^L, \delta\right\}$	$\min\left\{\delta^U, \delta\right\}$
	$\mu_h =$	μ	$\min\left\{\mu^L, \mu\right\}$	$\min\left\{\mu^U, \mu\right\}$

For instance, household h faces the macroprudential LTV limit λ with 75% probability, the lower internal limit λ^L with 15% probability, and the upper internal limit λ^U with 10%. Importantly, macroprudential BBMs are regulatory requirements and apply to all households, thus if a macroprudential limit is lower than an internal one, it is assumed that the former is binding.

Now that we have all the necessary elements, including the data in $q(X_t)$ and Z_t, as well as the parametrization of borrowing constraints in Λ_t, we proceed to estimate the hyperparameter vector Ξ. The estimation is carried out using the SMQ procedure described in Section 2.3, yielding the hyperparameter estimates reported in Table A.8 and the corresponding parameter distributions shown in Figure A.18 of Appendix A.5. We then simulate the model and plot the resulting quantiles $q\left(X_t^* | \Lambda_t; \Xi, Z_t\right)$ in Figure 5(b).

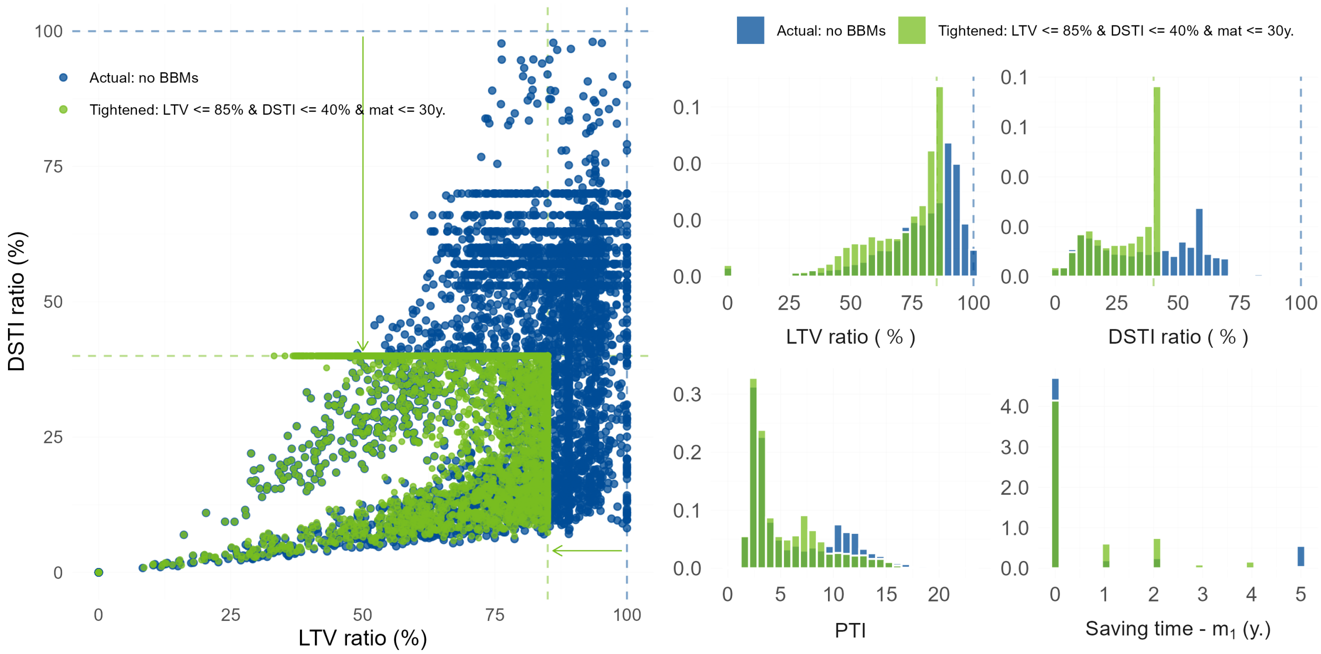
The model fits the data well, particularly the time series dynamics of the three key mortgage characteristics. The fit of the 75th and 90th percentiles is especially important, as our counterfactual analyses focus on mortgages with characteristics close to the BBM thresholds—in the upper part of the distribution. As shown in Figure 5(c), model fit varies across both BBM dimensions and time. The model tracks observed outcomes more closely during the regulatory period (2011–23), compared to the pre-regulation phase (2006–07). In the latter period, the model tends to underestimate LTV and DSTI ratios, suggesting that the estimated effects of a counterfactual tightening may be conservative, i.e., the true impact could be stronger. Conversely, during the regulatory period, the model slightly overestimates these ratios, potentially introducing a positive drift in counterfactual estimates, i.e., the true impact may be somewhat weaker.

3.1.3 Counterfactual I. 2006-07: Adoption of BBMs

To assess the impact of a hypothetical BBM adoption in the mid-2000s, we simulate household choices using the estimated model under two scenarios: actual—no BBMs (navy), and a counterfactual—full BBM package (green) with LTV and DSTI limits of 85% and 40%, and a 30-year maturity cap.

Figure 9: Simulated Household Distributions in 2006-07 in Lithuania: Adoption of BBMs

(a) LTV and DSTI scattergram (b) Histograms



Notes: Simulation of 500 households under no BBMs (navy) and under LTV $\leq$ 85%, DSTI $\leq$ 40%, mat. $\leq$ 30y. (green), with $\Delta^{m_1} = 12$ and $\Delta^{m_2} = 60$. Dashed horizontal and vertical lines represent actual (navy) and counterfactual (green) borrowing limits.

As shown in Figure 9, a significant share of borrowers with LTV ratios above 85% or DSTIs above 40% would have been constrained by the hypothetical policy, and would have had to re-optimize. This would result in lower debt uptake per affected household, bringing LTV and DSTI ratios down to the new limits. Additionally, the 30-year maturity cap would have prevent borrowers from unduly extending their loan terms and thus would have kept DTI ratios anchored. Borrower re-optimization is represented by the leftward shift in panel (b) histograms, with significant bunching at the LTV $\leq$ 85% and DSTI $\leq$ 40% hypothetical limits. Bunching at macroprudential limits has been documented empirically, for example by van Bekkum et al. (2024) in the context of the LTV cap introduction in the Netherlands. In aggregate, such a policy would have reduced the mortgage credit flow ($\sum_h D_h$) by 29%, and housing demand, measured by the aggregated house value choices ($\sum_h V_h$), by 13% (see Table 5a).[21]

The revised policy would entail interesting distributional changes. While the overall housing demand decreases, the demand for lower-valued housing increases, as can be seen from the leftward shift in the PTI histogram. For example, the share of households buying moderately-valued houses (PTI $\leq$ 8), instead of expensive ones (PTI $>$ 8), would have risen by 13 p.p. This finding aligns with empirical evidence for Israel (Tzur-Ilan, 2023) and Brazil (De Araujo et al., 2020). The hypothetical introduction of BBMs, including the LTV limit that necessitates a down payment, would also increase the saving-renting time, effectively postponing housing and credit

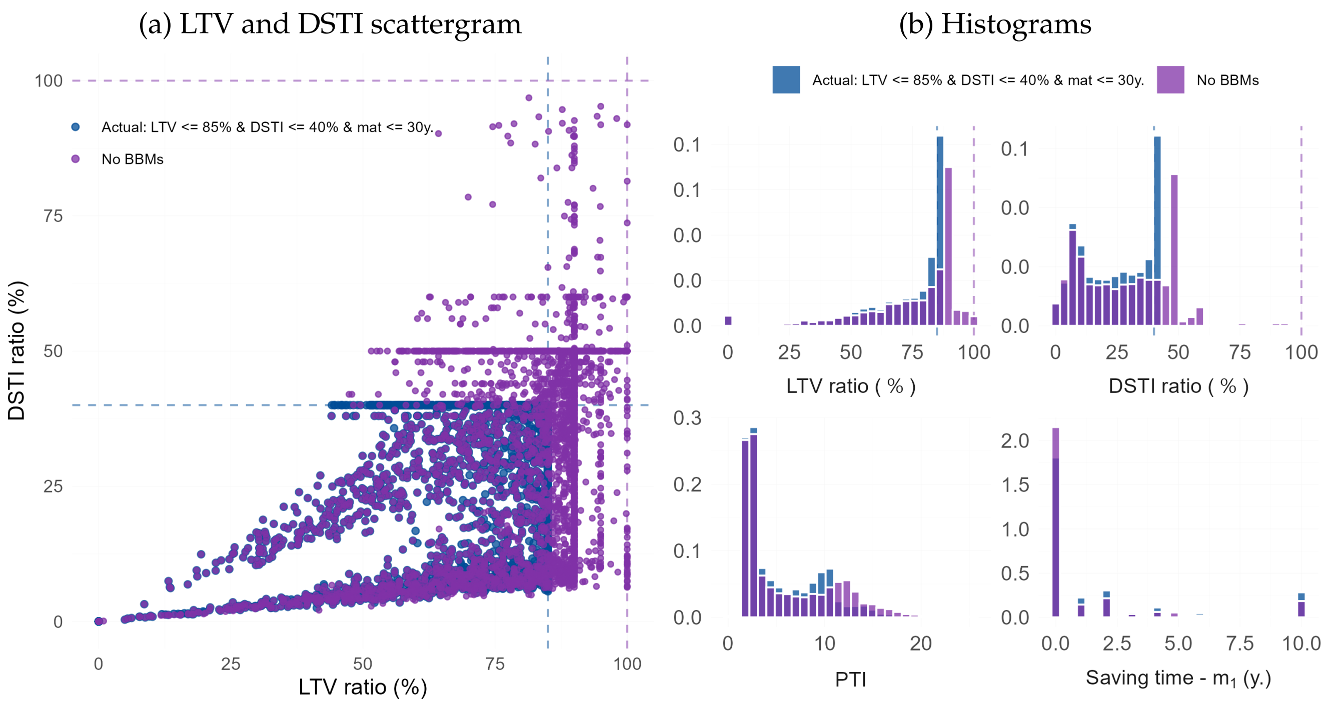
[21]Given the slight underestimation of LTV and DSTI ratios in the pre-regulatory period, the true impacts of BBM adoption may have been even larger.

demand by 17 months on average. As a result of this hypothetical regulation, aggregate lifetime expenses on rent ($\sum_h m_{1,h}\rho_h R_h$) would have effectively tripled.

3.1.4 Counterfactual II. 2011-20: No BBMs

During the second period of interest, household credit was constrained by the adopted BBM regulation, with mortgage and house price growth moderating relative to the pre-GFC period. To estimate the dampening effect of BBMs, we simulate households under the actual regulation, and under a counterfactual scenario with effectively no regulation—setting LTV and DSTI limits to 100% and maturity to 40 years (Figure 10).

Figure 10: Simulated Household Distributions in 2011-20 in Lithuania: No BBMs



Notes: Simulation of 500 households under actual BBMs (navy) and no BBMs (purple), with $\Delta^{m_1} = 30$ and $\Delta^{m_2} = 60$. Dashed horizontal and vertical lines represent actual (navy) and counterfactual (purple) borrowing limits.

As can be seen from the chart, households were already constrained by the existing regulation with LTV and DSTI ratios (navy points) boxed in by the respective limits.[22]. The spread-out purple points and rightward shifting histograms indicate that an abolition of BBMs would have increased housing credit uptake, up to the assumed internal limits (see Figure 8), with significant bunching at the LTV = 90% and DSTI = 50% points. Had the authorities lifted BBMs, mortgage credit flow could have increased by around 29%, with 16% higher aggregate house value choices

[22]The estimated model slightly overestimates the DSTI ratios, hence the bunching at the 40% limit in our simulations, which could produce larger than true impacts of BBM abolition

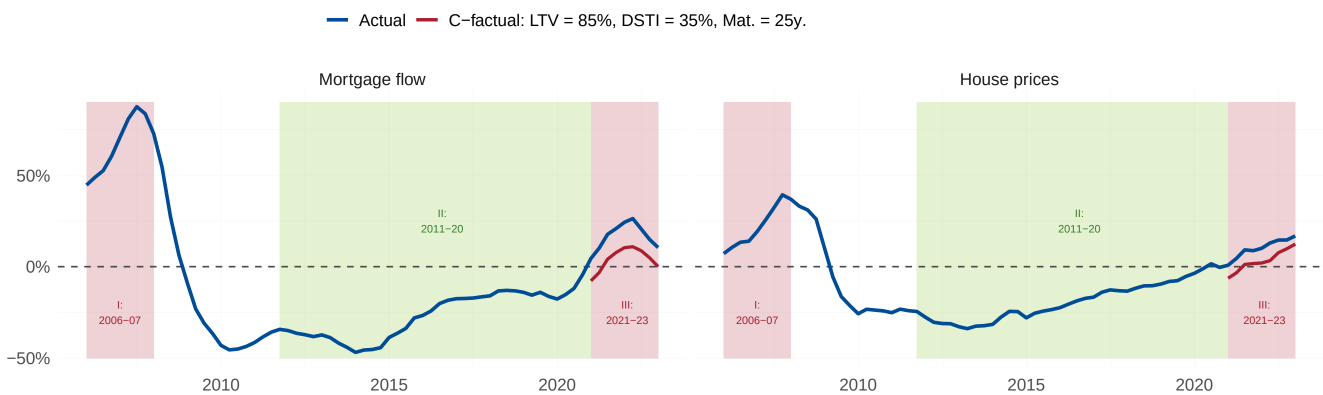
(see Table 5b).[23] In addition, simulations reveal that households would front-load their house purchases by entering the market around 10 months earlier.

3.1.5 Counterfactual III. 2021-23: More stringent BBMs

During the pandemic, Lithuania experienced a demand-driven housing boom, with mortgage lending and house prices rising by 23% and 18%, respectively. These dynamics appeared unsustainable, leading to a 16% misalignment in mortgage flow and a 10% home overvaluation (Figure 11). Had the ECB not raised interest rates—effectively halting the boom—a preemptive BBM tightening could have helped contain the emergence of imbalances in Lithuania.

Figure 11: Counterfactual Impact of BBM Packages in Lithuania

(a) Mortgage flow (b) House prices



Notes: Navy line represents misalignments based on Karmelavičius et al. (2022). Red lines represent simplified counterfactual estimates as percent deviations from the actual mortgage flow and house price levels.

We evaluate alternative BBM parametrizations that could have closed these gaps by leaning against the demand surge. Table 5 presents various BBM packages—combinations of LTV, DSTI, and maturity limits—and their estimated period-specific impact on mortgage credit and house value choices. While they are not exactly one-to-one comparisons to the observed aggregate credit flows and house prices, as we do not explicitly model supply, the tabulated values can still be informative on the magnitude of the policy impact.

Assuming stable fundamentals, closing the observed gaps would require a 14% reduction in mortgage flows and a 9% decline in house prices.[24] Tighter calibrations in Table 5 appear to overshoot these targets, with looser ones falling short. For example, a 5 p.p. tightening of the LTV limit might have broadly achieved the desired effect, but would have been quite distortive, as around half of borrowers were already at the 85% threshold and thus would have to postpone

[23] Assuming that lenders would not limit risk taking, abolition of BBMs could have resulted in doubling of monthly mortgage issuance.

[24] This is because the gap size and the level reduction rate Δ are based on different denominators: $\Delta = 1 - 1/(1 + \text{gap})$, with $14\% = 1 - 1/\,(1 + 0.16)$ and $9\% = 1 - 1/\,(1 + 0.10)$.

Table 5: Hypothetical Impact of BBM Packages in Lithuania

I. 2006-07

		Tightening														*
Limit	LTV (%)	75	80	80	85	85	85	85	85	85	85	85	90	90	90	100
	DSTI (%)	40	35	40	30	35	40	35	40	45	40	45	40	45	50	100
	Maturity (y.)	30	30	30	25	25	25	30	30	30	35	35	30	30	35	40
Impact	Credit (%)	-36	-37	-32	-43	-38	-33	-34	-29	-24	-26	-21	-26	-20	-12	0
	House v. (%)	-15	-17	-14	-20	-16	-13	-16	-13	-9	-14	-11	-12	-8	-6	0

II. 2011-20

		Tightening							*	Loosening						
Limit	LTV (%)	75	80	80	85	85	85	85	85	85	85	85	90	90	90	100
	DSTI (%)	40	35	40	30	35	40	35	40	45	40	45	40	45	50	100
	Maturity (y.)	30	30	30	25	25	25	30	30	30	35	35	30	30	35	40
Impact	Credit (%)	-15	-13	-8	-21	-14	-8	-7	0	5	1	6	7	15	21	29
	House v. (%)	-7	-8	-3	-12	-8	-4	-5	0	4	0	4	3	8	13	16

III. 2021-23

		Tightening							*	Loosening						
Limit	LTV (%)	75	80	80	85	85	85	85	85	85	85	85	90	90	90	100
	DSTI (%)	40	35	40	30	35	40	35	40	45	40	45	40	45	50	100
	Maturity (y.)	30	30	30	25	25	25	30	30	30	35	35	30	30	35	40
Impact	Credit (%)	-22	-16	-12	-17	-11	-6	-5	0	5	1	5	12	19	25	35
	House v. (%)	-14	-10	-7	-11	-7	-3	-4	0	3	0	3	7	12	16	22

Notes: Credit uptake and house value impact percentages compare against the actual regulation of the time represented by *. 10,000 household simulations per each quarter, using time series of Figure 7, hyperparameter estimates of Table A.8, with $\Delta^{m_1} = 60$ and $\Delta^{m_2} = 60$.

homeownership by around 10 months. By contrast, DSTI limits remained relatively loose due to the low interest rate environment, and thus would have been a more viable option for tightening due to less distortionary impact. The 85-35-25 package—reducing the DSTI limit by 5 p.p. and the maturity cap by 5 years while keeping the LTV at 85%—would have led to an 11% drop in mortgage uptake and a 7% decline in housing demand, effectively closing about four fifths of the gap in mortgage flow and postponing home purchases by merely 3 months.[25] These results are consistent with evidence showing that the LTV tightening reduced mortgage take up in Israel (Tzur-Ilan, 2023) and dampened credit and house price growth in Ireland (Cussen et al., 2015; Acharya et al., 2022; Castellanos et al., 2024), Lithuania (Reichenbachas, 2020), the UK (Kelly et al., 2018), Norway (Aastveit et al., 2021), Austria (Lindner and Albacete, 2017), and Korea (Igan and Kang, 2011). Likewise, Gatt (2024), using a purely theoretical model, shows that tightening the LTV limit lowers the homeownership rate, aggregate leverage, and house prices.

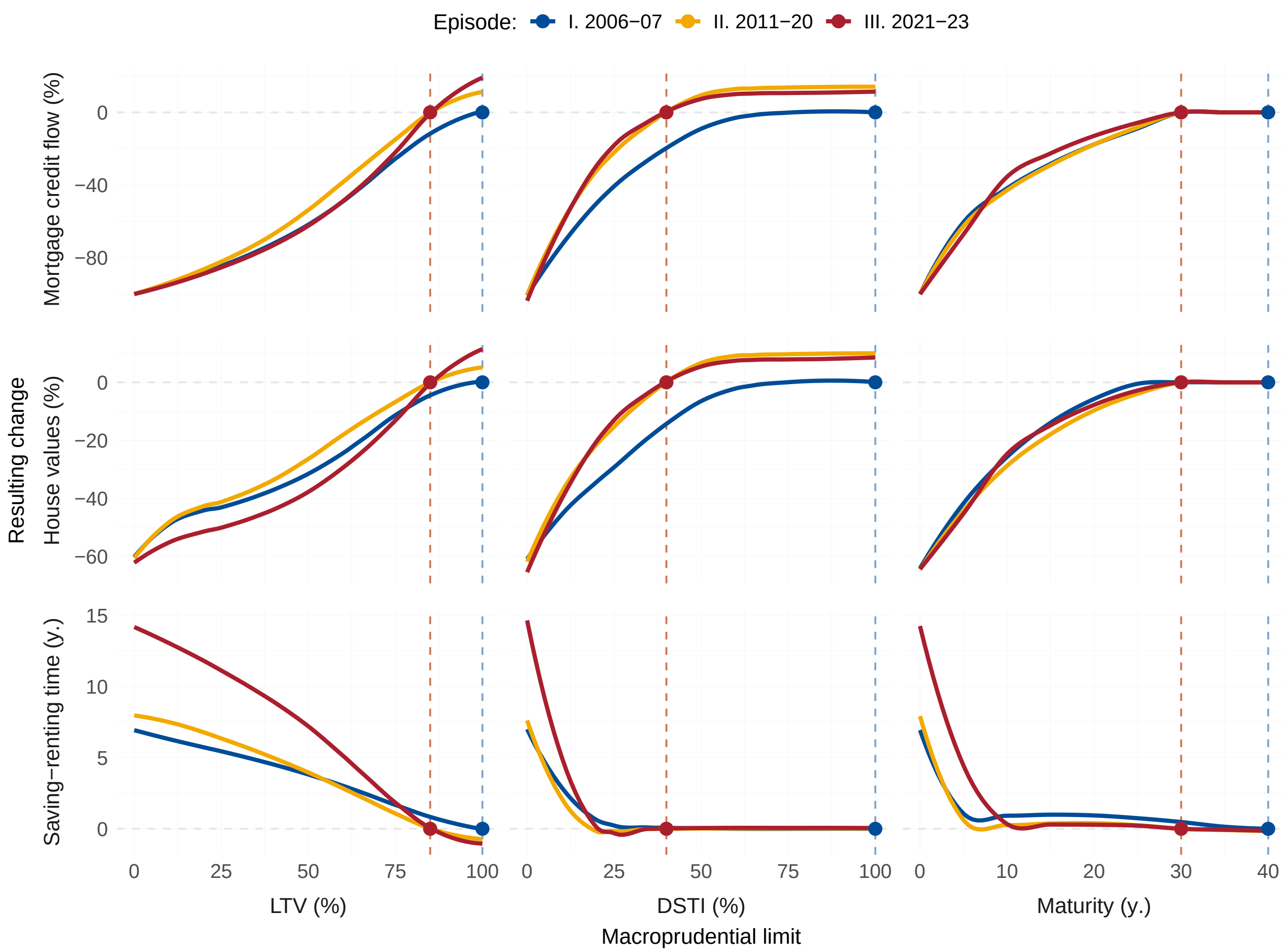
[25] The 85-35-25 calibration aligns with Dirma and Karmelavičius (2025) results that are based on a credit risk model. Since the model simulates slightly higher DSTI ratios than those observed, the true impact of the BBM package may have been somewhat smaller.

3.1.6 Discussion

The counterfactual exercises I–III reveal that BBMs can moderate credit and housing cycles by reducing demand, through lower debt uptake and house values, as well as delayed purchases. Conversely, the absence or relaxation of BBMs can amplify leverage and intensify credit-housing dynamics, with demand brought earlier. The effects of tightening, however, may have social implications, with households forced to rent for longer and settle for lower-quality housing.

More generally, we vary each BBM limit unilaterally over a grid: LTV and DSTI limits range from 0% to 100% in 5 p.p. steps, and maturity caps span from 0 to 40 years in 5-year increments. The model is then simulated across all periods (I–III) using this parameter grid, with impact on credit, house values, and saving-renting time depicted in Figure 12.

Figure 12: Counterfactual Impact of Unilateral Changes in Each BBM Limit in Lithuania



Notes: Each column of subplots refers to a simulation, in which a single borrowing limit (λ-δ-μ) is changed unilaterally (x-axis). The colored points and dashed vertical lines mark the actual macroprudential limits for each period (I-II-III), whereas the curves show the impact of counterfactual regulation (smoothed using *loess* with window span of 0.5). Simulations use time series (Z_t) data of Figure 7, hyperparameter estimates ($\hat{\Xi}$) of Table A.8, internal limits of Table 4 and Figure 8, with 10,000 households per each quarter. Durations grid $\nabla^m : \Delta^{m_1} = \Delta^{m_2} = 60$.

The chart illustrates that BBM effects are non-linear and state-dependent as they depend on both the instrument type and the underlying mortgage distribution, reflected by the differing curves across the three periods.[26] The impact is generally more pronounced for the LTV limit, as LTV ratios were by far the most binding in Lithuania. Notably, a 90% LTV limit would have been tightening in the 2000s but loosening during the BBM adoption era. As an own-funds requirement, the LTV limit has a more pronounced effect on saving and renting time than DSTI or maturity caps, since a higher down payment forces households to rent for longer while saving, thus delaying home purchases.

3.2 Case Study: Slovakia

3.2.1 Background

The second country to which we apply the model is Slovakia, which over the past two decades has experienced significant growth in household credit and a steady increase in house prices. While part of this reflected financial deepening and macroeconomic convergence—particularly following EU accession in 2004 and Euro Area entry in 2009—at times the pace of growth was assessed as excessive.

To address emerging risks, the National Bank of Slovakia (NBS) has actively used macroprudential policy, especially BBMs. In 2014, it issued a non-binding recommendation on LTV, DSTI, and maturity limits, which became binding and progressively tighter from 2017 onward, including the introduction of a DTI cap (see timeline in Figure 13).[27]

Figure 14 suggests that BBMs helped curtail mortgage risks by containing LTV, DSTI, and DTI ratios and maturities.[28] The DTI ratio remained relatively stable from 2018-22, with the 90th percentile falling below 8. As the stricter DTI limit took effect in 2023, the median dropped and the distribution narrowed, indicating increased bindingness.

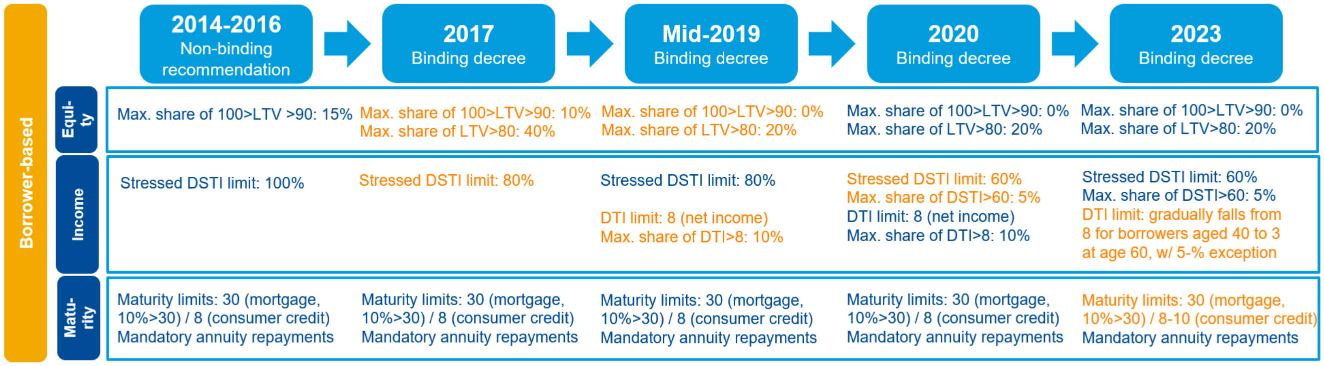
The DSTI cap, tightened several times, reduced both the median and upper percentiles. Since 2022, rising interest payments have pushed the median and 75th percentile upward, with the 90th percentile hitting the 60% cap. The LTV limit has remained stable, with the median around 70% and the 75th percentile at the 80% threshold for most loans. Maturities have neared the 30-year cap, especially as borrowers stretched terms to offset rising interest costs.

[26] Given that the model omits equilibrium feedback effects, the true impact of BBM changes on credit may be stronger than discussed. For instance, loosening BBMs raises house value choices, which under a model with market-clearing conditions would increase reservation values a_t, further amplifying house values and credit (see eqs. A.22, A.28).

[27] The BBM calibration—featuring exemptions, speed limits, and age-based DTI differentiation—is based on the NBS's micro-macro model (see Jurča et al., 2020), which uses loan-level data to simulate borrower income streams and risk parameters under adverse macrofinancial scenarios.

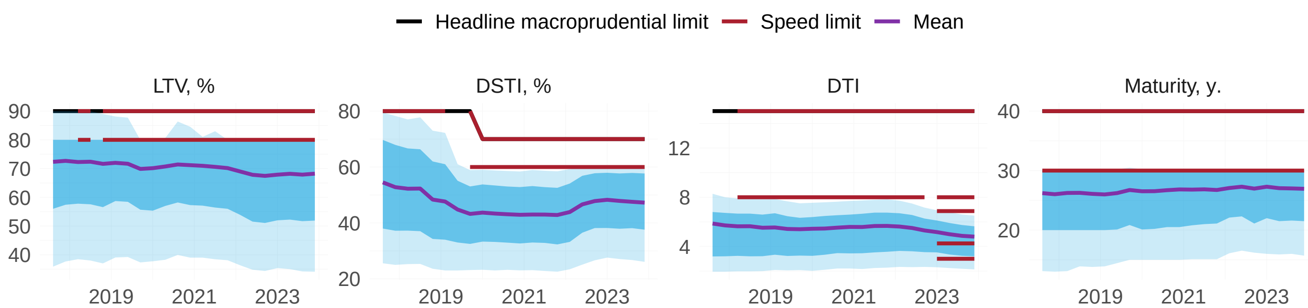
[28] This assessment is confirmed by comprehensive *ex post* evaluations in Jurča et al. (2020) and IMF (2021).

Figure 13: Timeline of Borrower-Based Measures in Slovakia



Source: Update of the table in Pavol Jurča's presentation on "The effectiveness of combinations of borrower-based measures: a quantitative analysis for Slovakia" at the Joint Banca d'Italia and European Central Bank Research Workshop, Rome, 10 October 2019, based on the NBS Discussion Note "Index of borrower-based measures in Slovakia", the IMF's Macroprudential Survey, and the NBS's website.

Figure 14: Macroprudential BBM limits in Slovakia



Notes: The shaded areas represent the 25th-75th and the 10th-90th percentiles of actual mortgage issuance, taken from Figure 15(a).

The Slovak BBM framework includes various exemptions and speed limits. As of 2024, the headline LTV limit was set at 80%, with 20% of loans allowed up to 90% LTV. The stressed DSTI limit stood at 60%, with a 5% exemption up to 70%. The DTI limit was age-dependent, ranging from 8 for borrowers aged 40-and-under to 3 for those aged 60-and-over, with a 5% exception. Mortgage maturities were capped at 30 years, with a 10% exception.

While these exemptions introduce flexibility, they are not formally linked to borrower characteristics, such as FTB status, leaving their allocation to lender discretion. This can be inferior from both risk-management and social perspectives. Empirical evidence shows that FTBs tend to have lower default rates and contribute less to credit booms than second-time buyers (STBs, e.g., Kelly et al., 2015; Lazarov and Hinterschweiger, 2018; Giuliana, 2019; Nier et al., 2019). Investor and BTL loans are the riskiest and most procyclical segments, because repayment depends on volatile rental income and borrowers often hold multiple leveraged properties (Lazarov and Hinterschweiger, 2018; Baptista et al., 2016; Tarne et al., 2022). Nevertheless, banks may favor them due to higher interest margins, stronger collateral values, and perceived borrower sophistication. From a distributional perspective, ensuring that mortgage markets remain accessible to younger and lower-income households is often desirable, but lenders may lack incentives to allocate them accordingly.

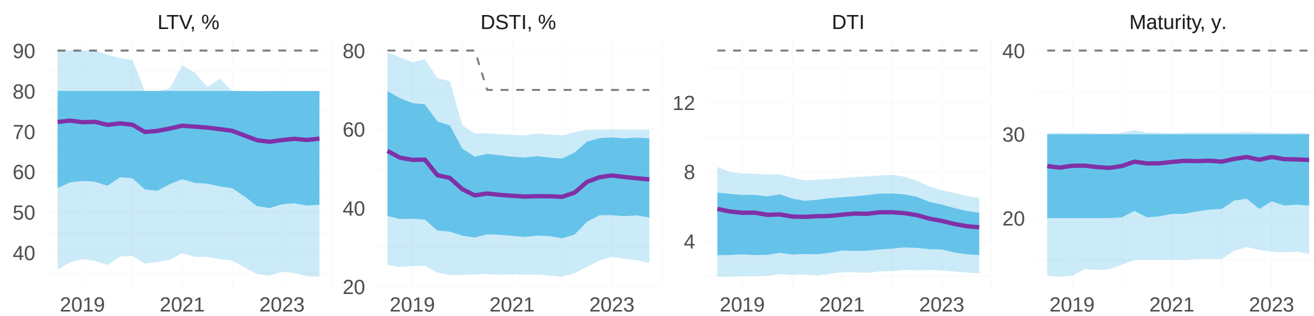
This subsection applies the model to Slovakia and illustrates how BBMs could be streamlined by differentiating LTV limits by borrower type, providing quantitative estimates of the resulting effects on credit uptake and house prices. The analysis provided inputs to the IMF's 2025 Financial Sector Assessment Program for Slovakia (IMF, 2025).

3.2.2 Modifying and Estimating the Model

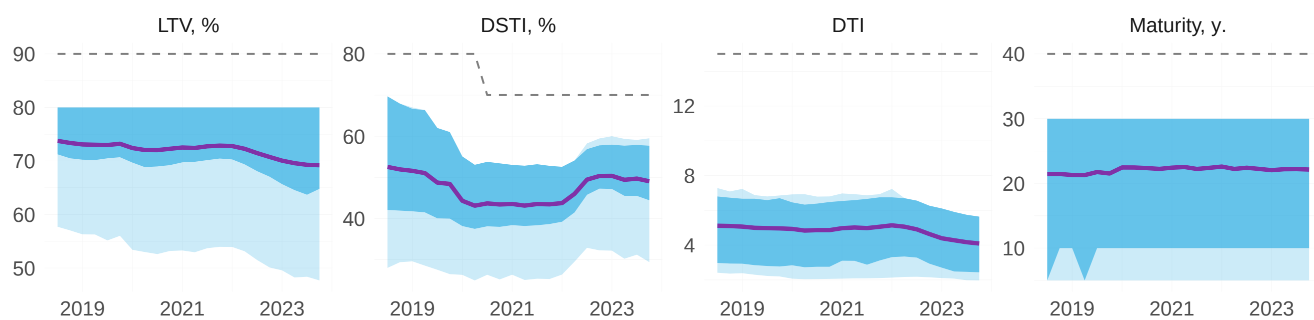
To bring the model to Slovak data, we follow a similar procedure as in Lithuania's case by using actual distributions of LTV, DSTI, DTI, and maturity (Figure 15a) as our target variables $q(X_t)$ for the SMQ, and exogenous variables (Z_t, Figure 16) as drivers of simulation dynamics.

Figure 15: Distributions for New Mortgage Lending in Slovakia

(a) Actual series



(b) Model-simulated series



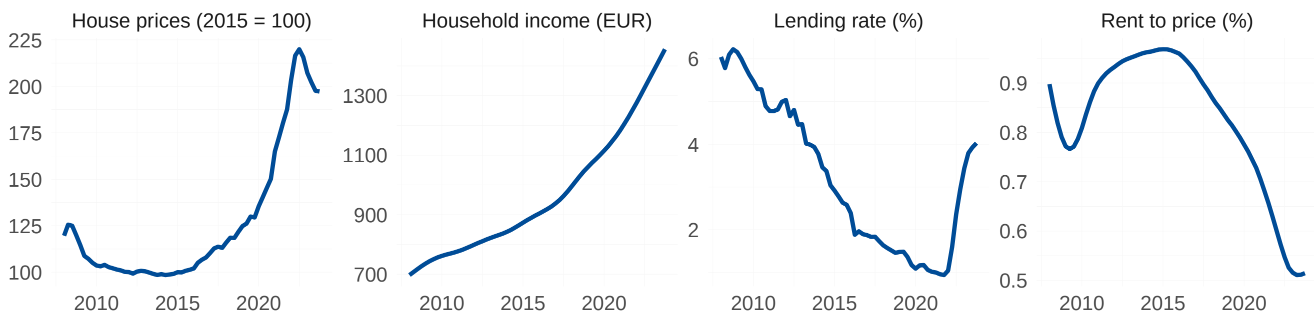
(c) Model fit (Root Mean Squared Error, RMSE)

	LTV (p.p.)			DSTI (p.p.)			DTI			Maturity (y.)		
Percentile	Median	75th	90th	Median	75th	90th	Median	75th	90th	Median	75th	90th
RMSE	5.6	0.0	5.5	2.8	0.0	6.8	0.1	0.0	0.1	1.8	0.0	0.3

Notes: Purple lines mark averages, the shaded areas – 25th-75th and 10th-90th percentiles, and dashed lines – headline BBM limits. The simulated series in (b) are based on Z_t time series of Figure 16, Λ_t limits of Figure 14, and hyperparameter $\hat{\Xi}$ estimates of Table A.8. We assume 10,000 household simulations per each quarter, with $\Delta^{m_1} = 12$ and $\Delta^{m_2} = 60$.

However, Slovak BBMs feature a number of particularities relative to the more standard model, which we need to adjust for that.

Figure 16: Exogenous Time Series Data for Slovakia



First, a minimum subsistence (S) is deducted from income in the definition of the DSTI ratio:

$$\frac{Df(i,m_2)}{I_2 - S} \leq \delta^*.$$

Second, there is a stressed DSTI requirement, where the DSTI is based on a stressed rate (i^{st}: actual rate plus 2 p.p., capped at 6%) and the maximum maturity:

$$\frac{Df(i^{st},m_2^{st})}{I_2 - S} \leq \delta^*, \text{ with } i^{st} := \min\{i + 0.02; 0.06\}, \text{ and } m_2^{st} := 30 \cdot 12.$$

Third, there is an additional debt-to-income (DTI, κ) requirement:

$$\frac{D}{12I_2} \leq \kappa.$$

The DSTI constraint in the original model is:

$$\frac{Df(i,m_2)}{I_2} \leq \delta.$$

Therefore, for each household h, we transform limits (δ^*, κ) to the effective limit (δ_h) relevant for the original model:

$$\delta_h = \min\left\{\delta^* \cdot \left(\frac{I_{2h} - S_h}{I_{2h}}\right); \quad \delta^* \cdot \left(\frac{I_{2h} - S_h}{I_{2h}}\right) \cdot \frac{f(i_h, m_{2h})}{f(i_h^{st}, m_{2h}^{st})}; \quad \kappa \cdot f(i_h, m_{2h}) \cdot 12\right\}.$$

Finally, all BBMs are subject to exemptions or speed limits. This multidimensionality in limits is tackled by applying each BBM limit to randomly-drawn borrowers, using exempt borrower share as probability (see Figure 14 and Table B.1).

The model is estimated with hyperparameter estimates depicted in Appendix B Figure B.1, while the fitted series of Slovak data are depicted in Figure 15b. Model simulations track the actual distributions quite closely in terms of time series dynamics and upper quantiles. There is some underestimation of the LTV, DSTI, and DTI ratios, however, which could lead to a slight underestimation of the tightening impact.

3.2.3 Counterfactual: Redesigning Speed Limits

Before exploring BBM differentiation and their impact, we take a look at how LTV regulation affects liquidity constrained households. Here we define liquidity-constrained as simulated households with initial assets-to-income ratio at the bottom 40% of household population, and the unconstrained as the top 40%.[29]

Figure 17 illustrates the effects of a unilateral LTV change based on Slovak data. As before, we find that tight LTV regulation can lead to lower credit and house value choices, as well as households having to rent for a long time. This result is more pertinent for liquidity-constrained households whose homeownership chances could decrease and lifetime rental expenses increase quite significantly in response to LTV tightenings. This finding is consistent with evidence that BBMs tend to be more restrictive for younger and lower-income households, which are typically more liquidity constrained (Castellanos et al., 2024; Yao et al., 2015; Oliveira and Queiró, 2023; Lindner and Albacete, 2017).

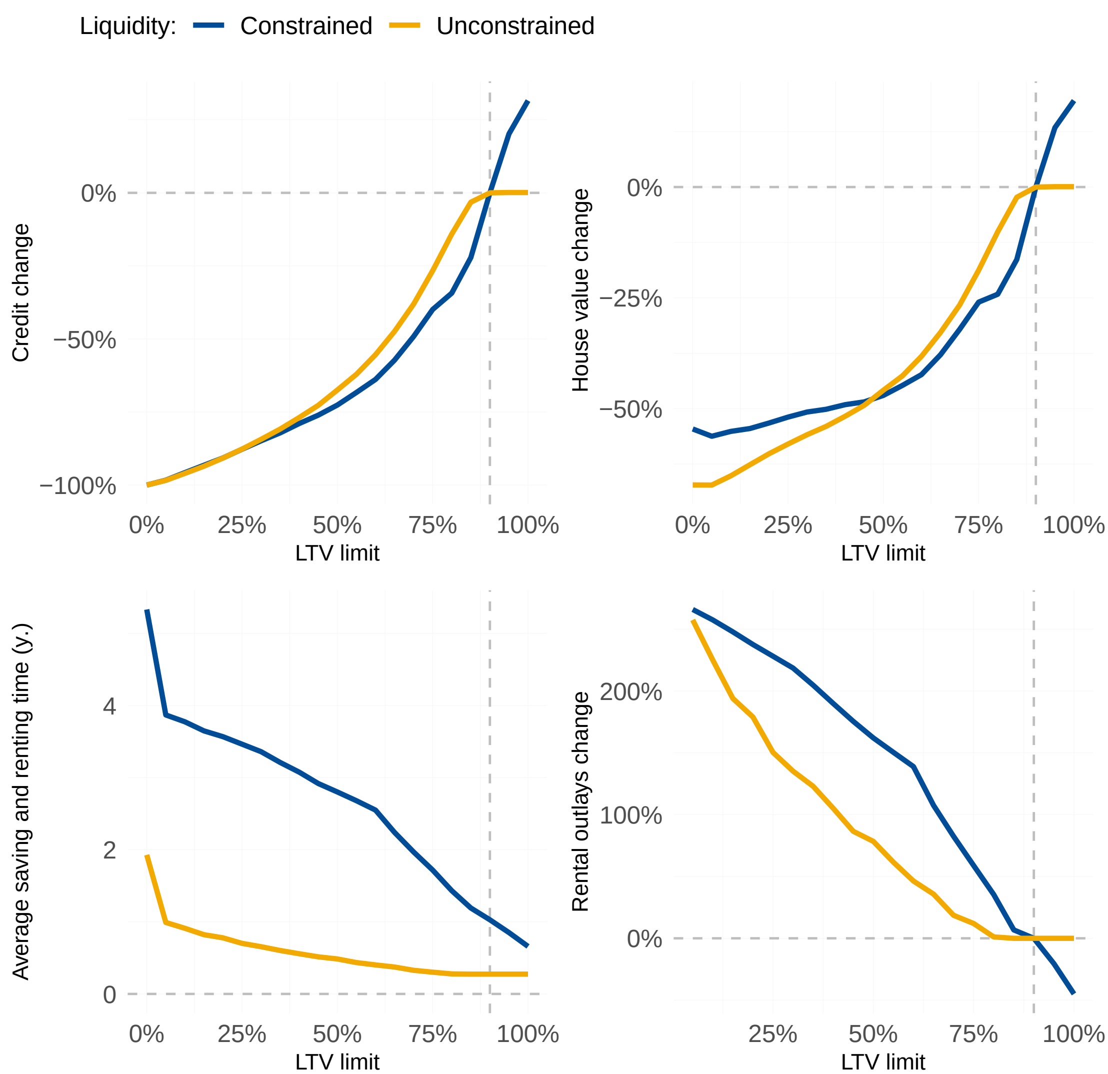
While the framework is not able to assess welfare, the discussion highlights potential implications for access to credit across household groups. If such distributional effects are deemed undesirable, they could be mitigated by smart design choices, such as differentiating LTVs by borrower characteristics. Indeed, many countries apply a differentiated approach to BBMs, tailoring limits to borrower profiles and their associated contribution to systemic risk.[30] This places the regulator in control of differentiation, rather than allowing lenders to use discretion in application of exemptions.

In the following, we compute the effects of different packages that differentiate the LTV based on these borrower categories while ceasing other DSTI, DTI, and maturity exemptions. While the framework does not explicitly differentiate between FTBs, STBs, and investors, it allows for calibration of household subgroups to reflect observed population shares and the application of distinct borrower-based limits. We use the model to quantify the recently used package's dampening effect on credit uptake and house value choices, relative to counterfactual scenarios with several alternative packages. The period under consideration is from 2020Q3 to 2023Q4, which includes the time when credit growth rebounded after the slump at the beginning of the pandemic.

[29] The results do not change when narrower definitions of the liquidity-constrained are applied (e.g., bottom 20%).

[30] For example, Finland, Hungary, Iceland, and Luxembourg have higher LTV limits for FTBs, while Belgium, Cyprus, Ireland, Latvia, and Romania have stricter LTV limits for BTL.

Figure 17: Social Impacts of LTV Regulation



Notes: Constrained households are defined as the bottom 40% of A_0/I_2 distribution, unconstrained – top 40% of the distribution. Aggregate saving and renting time defined as $\sum_h m_{1,h}$, rental outlays as $\sum_h m_{1,h}\rho_h R_h$. Based on simulations of 10,000 heterogeneous households, with durations grid ∇^m: $\Delta^{m_1} = 3$ and $\Delta^{m_2} = 12$, Λ_t limits of Figure 14, Z_t time series of Figure 16, and hyperparameter $\hat{\Xi}$ estimates of Table B.2.

Table 6 presents various options arranged in ascending order based on their tightening impact. Compared to the current BBM regulation, Option 1 eliminates exemptions for the 60% DSTI limit, establishes a maturity limit of 30 years, includes an age-independent DTI of 8, and assumes that FTBs have an LTV limit of 90%, while all other borrowers are subject to an 80% limit. This option represents a regulatory package with similar stringency to the current regulations but excludes exemptions and differentiates LTV limits based on borrower type.

In comparison, Option 2 introduces a tighter LTV for investors, BTL borrowers, and those seeking equity withdrawal or top-ups. This aims to mitigate the procyclicality typically associated with these categories, thereby somewhat helping to reduce the growth in credit and house values. Option 3 implements an even stricter LTV for equity withdrawal or top-ups, as this

Table 6: Counterfactual Impact of Different BBM Packages in Slovakia

			⟶*Tightening*⟶						
			Opt. 1	Opt. 2	Opt. 3	Opt. 4	Opt. 5	Opt. 6	Opt. 7
Limit	LTV, %	FTBs	90	90	90	85	80	80	80
		STBs	80	80	80	80	80	80	75
		Investors	80	70	70	70	70	70	70
		Top ups	80	70	50	50	50	50	50
	DSTI, %		60	60	60	60	60	55	55
	Maturity, y.		30	30	30	30	30	30	30
	DTI		8	8	8	8	8	6	6
Impact	Credit (%)		1	-4	-6	-6	-8	-12	-15
	House v. (%)		1	-2	-3	-3	-3	-5	-7

Notes: The table presents various BBM package redesigns in ascending order based on their tightening impact. Simulations of 5,000 heterogeneous households, with durations grid ∇^m: $\Delta^{m_1} = 60$ and $\Delta^{m_2} = 60$, Z_t time series of Figure 16, and hyperparameters $\hat{\Xi}$ of Table B.2.

behavior can be highly procyclical, leading to a slightly greater reduction in credit uptake and house values.

While Options 1-3 maintain a relatively high LTV of 90% for FTBs, the subsequent options consider tightening this limit as well as modifying other thresholds. Simply lowering the LTV for FTBs to 85% does not significantly affect credit or house value choices, as only a small proportion of lending falls within the 85%-90% LTV range. However, if the DTI is also tightened to 6—closer to the current average—this results in an additional reduction in both house values and credit uptake.

In summary, a streamlined regulatory framework, free of exemptions for income-based measures and the maturity limit, combined with LTV differentiation by segment, can have a significant effect on curbing credit and housing demand while aiming to reduce procyclicality and enhance the resilience of certain borrower types.

4 Conclusions

Quantifying the impact of macroprudential BBMs requires not only granular data on mortgage distributions but also a rigorous framework to understand borrower behavior under changing conditions. This paper develops such a framework, grounded in a life-cycle model, which enables the analysis of both aggregate and distributional effects of counterfactual policy changes on housing and credit demand.

In our setting, BBMs influence household behavior not only in magnitude but also in timing—shaping decisions about when to enter the housing market, how much to borrow, and how much to spend on housing. The model can be adapted to the circumstances prevailing in any country with sufficiently rich distributional mortgage data. We apply it to Lithuania and Slovakia, yielding several key insights with broader relevance.

Well-calibrated BBMs can help smooth credit and housing cycles by reducing and postponing credit uptake and housing demand. These effects are non-linear and sensitive to initial conditions. Conversely, lax limits—or the absence of BBMs—effectively amount to self-regulation, which may result in increased leverage, front-loaded demand, and upward pressure on home valuations.

Nonetheless, caution is warranted. Stringent BBMs can produce outcomes that may be viewed as undesirable from a broader perspective, such as households being pushed into lower-quality housing, reduced homeownership rates, and increased pressure on rental markets. Because these effects are unevenly distributed and disproportionately borne by financially constrained households, regulation should be designed to preserve financial stability while recognizing distributional impacts and the potential for tailoring measures to borrower characteristics. For instance, LTV limits could be differentiated by borrower type, as implemented in several countries.

While our micro-founded framework models household behavior under three simultaneous borrowing constraints, it does not capture all relevant factors. Notably, default is not modeled, precluding analysis of household resilience, a topic addressed in a separate literature. Similarly, housing is not treated as an investment asset, and we abstract from housing supply and equilibrium feedback effects. Although these factors undoubtedly influence mortgage and housing dynamics, evidence suggests that demand-side drivers have been the primary determinants of short- to medium-term developments in many contexts. Ultimately, we view this framework as a useful foundation for analyzing direct impacts on borrower behavior, with scope for future research to build on it.

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Appendix A Model Solution

A.1 First-Order Conditions

The associated Lagrangian is the following:

$$\begin{aligned}\mathcal{L} = & \, m_1 U_1(C_1, R) + m_2 \beta_2 U_2(C_2, V) + (T - m_1 - m_2)\beta_3 U_3\left(I_3, V\right) + \\ & + \tau_1 \left(A_0 g(r_A, m_1) + z(r_d, m_1)(I_1 - C_1 - \rho R) + \frac{I_2 - C_2}{f(i, m_2)} - V \right) + \\ & + \tau_2 \left(\lambda - \frac{I_2 - C_2}{V f(i, m_2)} \right) + \tau_3 \left(\delta - \frac{I_2 - C_2}{I_2} \right) + \tau_4 \left(\mu - m_2 \right),\end{aligned}$$

where $\tau_1, \tau_2, \tau_3, \tau_4$ are Lagrange multipliers. The first-order conditions of the Kuhn-Tucker problem are the following:

$$\frac{m_1}{C_1} = z(r_d, m_1)\tau_1, \tag{A.1}$$

$$\frac{m_1 \theta_1}{R - a_1} = z(r_d, m_1)\rho\tau_1, \tag{A.2}$$

$$\frac{m_2 \beta_2}{C_2} - \frac{\tau_1}{f(i, m_2)} + \frac{\tau_2}{V f(i, m_2)} + \frac{\tau_3}{I_2} = 0, \tag{A.3}$$

$$\frac{m_2 \beta_2 \theta_2}{V - a_2} + (T - m_1 - m_2)\frac{\beta_3 \theta_3}{V - a_3} - \tau_1 + \frac{\tau_2 (I_2 - C_2)}{V^2 f(i, m_2)} = 0, \tag{A.4}$$

$$\begin{aligned}& \log C_1 + \theta_1 \log\left(R - a_1\right) - \beta_3 \left(\log I_3 + \theta_3 \log\left(V - a_3\right)\right) + \\ & \qquad + \tau_1 A_0 \frac{\partial g(r_A, m_1)}{\partial m_1} + \tau_1 \left(I_1 - C_1 - \rho R\right) \frac{\partial z(r_d, m_1)}{\partial m_1} = 0,\end{aligned} \tag{A.5}$$

$$\begin{aligned}& \beta_2 \left(\log C_2 + \theta_2 \log\left(V - a_2\right)\right) - \beta_3 \left(\log I_3 + \theta_3 \log\left(V - a_3\right)\right) - \\ & \qquad - \tau_1 \frac{I_2 - C_2}{f(i, m_2)^2} \cdot \frac{\partial f(i, m_2)}{\partial m_2} + \tau_2 \frac{I_2 - C_2}{V f(i, m_2)^2} \cdot \frac{\partial f(i, m_2)}{\partial m_2} - \tau_4 = 0\end{aligned} \tag{A.6}$$

$$A_0 g(r_A, m_1) + z(r_d, m_1)(I_1 - C_1 - \rho R) + \frac{I_2 - C_2}{f(i, m_2)} = V, \tag{A.7}$$

$$\tau_2 \left(\lambda - \frac{I_2 - C_2}{V f(i, m_2)} \right) = 0, \tag{A.8}$$

$$\tau_3 \left(\delta - \frac{I_2 - C_2}{I_2} \right) = 0, \tag{A.9}$$

$$\tau_4 (\mu - m_2) = 0, \tag{A.10}$$

$$\lambda \geq \frac{I_2 - C_2}{V f(i, m_2)}, \tag{A.11}$$

$$\delta \geq \frac{I_2 - C_2}{I_2}, \tag{A.12}$$

$$\mu \geq m_2, \tag{A.13}$$

$$\tau_2 \geq 0, \tag{A.14}$$

$$\tau_3 \geq 0, \tag{A.15}$$

$$\tau_4 \geq 0. \tag{A.16}$$

Functions g, z, and f are defined in equations (2), (3), and (6), with $\partial \cdot / \partial m_t$ referring to their partial derivatives with respect to durations m_1 and m_2. Complementary slackness conditions (A.8)-(A.10) imply that either the borrowing constraints are binding with equality, or the respective Lagrange multipliers (τ_2, τ_3, τ_4) are zero, indicating constraint slackness. Each τ's magnitude corresponds to the shadow value of relaxing the associated borrowing constraint.

A.2 Solution Strategy

The latter system is comprised of 16 non-linear expressions, among which are 6 inequalities and 10 equations, involving 10 endogenous control variables ($C_1, C_2, R, V, \tau_1, \tau_2, \tau_3, \tau_4, m_1, m_2$). The solution of the complex non-linear system entails finding optimal values for the control variables, such that all constraints are satisfied. Note that the non-linear complexity of the system is primarily associated with durations m_1 and m_2, which enter the model as exponential functions (g, z, f) and their derivatives. To solve the model for each optimizing borrower, we need to address this non-linearity, as well as to deal with the inequalities.

To tackle the non-linearity in m_t, we use a combination of numerical and analytical methods. First, we generate a grid ∇^m of m_1 and m_2 values as well as $m_3 \equiv T - m_1 - m_2$, such that $m_1 + m_2 \leq T$ and $m_2 \leq \mu$, using Δ^{m_t} increments from 0 to T, thereby nesting corner cases where any life stage can be void, e.g, $m_1 = 0$, $m_2 = 0$, or $m_3 = 0$.[31] Then, we iterate over the grid by fixing the generated m_t values – assuming that durations of each life stage are optimal, and proceed by analytically solving the rest of the model, excluding equations (A.5) and (A.6).

To deal with inequalities, we partition the solution space into scenarios in terms of bindingness of the LTV and DSTI borrowing constraints (eq. 9 and 10), assuming that the grid-generated loan term m_2 ($\leq \mu$) is optimal. Specifically, either LTV, or DSTI, or both, or none of the two constraints may be binding, as tabulated in Table A.7.

The overall solution of the system would entail finding analytical solutions for each of the four scenarios, and choosing a combination of a scenario and life stage durations that would result in maximum lifetime utility (U of eq. 13), such that all constraints are satisfied.

[31] In our empirical applications (Section 3), we assume a 1-year increment for the duration of renting and saving ($\Delta^{m_1} = 12$), and a 5-year increment for mortgage duration ($\Delta^{m_2} = 5 \cdot 12 = 60$). While single-household optimization depends on the increment size, the results for a large number of heterogeneous borrowers are less sensitive to Δ^{m_t}.

Table A.7: Scenarios for LTV and DSTI Limit Bindingness

		DSTI binding	
		Yes	No
LTV binding	Yes	C	A
	No	B	D

A.3 Scenarios

Under a given scenario, if a borrowing constraint is binding, we treat the associated inequality–(A.11) for LTV and (A.12) for DSTI–as if it were an equality constraint, and solve the model. If the constraint is not binding, we assume strict inequality, solving for the rest of the model.

Scenario A: LTV binding, DSTI not

Under this scenario, we assume that

$$\lambda = \frac{I_2 - C_2}{Vf(i, m_2)} \text{ and } \delta > \frac{I_2 - C_2}{I_2},$$

implying that $\tau_2 > 0$ and $\tau_3 = 0$. We plug $\lambda = \frac{I_2 - C_2}{Vf(i,m_2)}$ and $\tau_3 = 0$ into the system and use equations (A.1)-(A.4) and (A.7) to solve for C_2, C_1, and V:

$$C_2 = \frac{-\mathbb{B} + \sqrt{\mathbb{B}^2 - 4\mathbb{A}\mathbb{C}}}{2\mathbb{A}}, \tag{A.17}$$

$$C_1 = \frac{m_1(1-\lambda)(I_2 - C_2 - a_2\lambda f)C_2}{z\lambda f\left(\Gamma_2 C_2 - \beta_2 m_2\left(I_2 - C_2 - a_2\lambda f\right)\right)}, \tag{A.18}$$

$$V = \frac{I_2 - C_2}{\lambda f}. \tag{A.19}$$

To save space, we make use of the following notations:

$$g \equiv g(r_A, m_1), \quad z \equiv z(r_d, m_1), \quad f \equiv f(i, m_2),$$
$$\mathbb{A} := (1-\lambda)\left((\Gamma_2 + \beta_2 m_2) + (1+\theta_1)m_1\right),$$
$$\mathbb{B} := \lambda f \Gamma_1(\Gamma_2 + \beta_2 m_2) - (1-\lambda)(I_2 - a_2\lambda f)\left(\beta_2 m_2 + (1+\theta_1)m_1\right),$$
$$\mathbb{C} := -\lambda f \Gamma_1 \beta_2 m_2 (I_2 - a_2\lambda f),$$
$$\Gamma_1 := A_0 g + z(I_1 - \rho a_1) - \frac{I_2(1-\lambda)}{\lambda f}, \quad \Gamma_2 := \beta_2 m_2 \theta_2 + \beta_3(T - m_1 - m_2)\theta_3.$$

Scenario B: DSTI binding, LTV not

Here the assumptions are exactly the opposite of scenario A's:

$$\delta = \frac{I_2 - C_2}{I_2} \text{ and } \lambda > \frac{I_2 - C_2}{Vf(i, m_2)},$$

which implies that $\tau_2 = 0$ and $\tau_3 > 0$. We use $C_2 = (1-\delta)I_2$, $\tau_2 = 0$, as well as equations (A.1)-(A.4), and (A.7), to solve for C_2, C_1, and V:

$$C_2 = (1-\delta)I_2, \tag{A.20}$$

$$C_1 = \frac{m_1}{z}\left[\frac{\frac{\delta I_2}{f} + A_0 g + z(I_1 - \rho a_1) - a_2}{m_1(1+\theta_1) + \Gamma_2}\right], \tag{A.21}$$

$$V = a_2 + C_1 \frac{z}{m_1}\Gamma_2. \tag{A.22}$$

Scenario C: both binding

In this case, both DSTI and LTV constraints are binding, implying that $V = \frac{\delta I_2}{\lambda f}$ and $C_2 = (1-\delta)I_2$, as well as $\tau_2 > 0, \tau_3 > 0$. Using these, we transform the system to get the following the solution:

$$C_2 = (1-\delta)I_2, \tag{A.23}$$

$$C_1 = \frac{\frac{A_0 g}{z} + I_1 - \rho a_1}{1+\theta_1} + \frac{\delta I_2}{zf(1+\theta_1)}\left(1 - \frac{1}{\lambda}\right), \tag{A.24}$$

$$V = \frac{\delta I_2}{\lambda f}. \tag{A.25}$$

Scenario D: neither binding

Here we assume that neither of the two borrowing constraints are binding, so that $\tau_2 = \tau_3 = 0$. Under this scenario, the model solution is the following:

$$C_2 = \frac{\beta_2 m_2 \left[f\left(A_0 g + z(I_1 - \rho a_1) - a_2\right) + I_2\right]}{m_1(1+\theta_1) + m_2\beta_2 + \Gamma_2}, \tag{A.26}$$

$$C_1 = \frac{m_1 C_2}{\beta_2 m_2 z f}, \tag{A.27}$$

$$V = a_2 + C_1 \frac{z}{m_1}\Gamma_2. \tag{A.28}$$

Full Solution

Now that we have partial solutions under all scenarios with fixed durations, we can find the general solution, which attains the highest lifetime utility for the household. To do so, we need to compute the lifetime utility function, as defined in equations (12) and (13), plugging in the solutions for C_1, C_2, and V, as well as the expression for rental house value R that is constant across all scenarios and corner cases:[32]

$$R = a_1 + \frac{\theta_1}{\rho} C_1. \tag{A.29}$$

Let partitioning $\Omega := \{\Omega_A, \Omega_B, \Omega_C, \Omega_D\}$ define the four scenarios. For given durations $m_t \in \nabla^m$ and a scenario $\Omega_J \in \Omega$, the partial solutions based on (A.17)-(A.28) and (A.29) are denoted as:

$$X^* (m_t, \Omega_J) := \underset{X \in \mathcal{X}_\Lambda}{\arg\max}\, U(X|\Theta; m_t, \Omega_J)$$

where Λ are borrowing limits and Θ are model parameters, X is the vector of control variables, and $\mathcal{X}_\Lambda$ is the constrained space – all defined in Section 2.1.4. The utility-maximizing life stage durations and scenario would be:

$$\left\{ m_t^*, \Omega_J^* \right\} := \underset{m_t \in \nabla^m,\ \Omega_J \in \Omega}{\arg\max} \quad U\left(X^*\left(m_t, \Omega_J\right)\right).$$

Then, the full model solution is $X^* := X^* \left(m_t^*, \Omega_J^* \right)$.

A.4 Corner Cases

Here we discuss various cases, in which the partial solutions of the model are not well-defined. For example, the partial solution under scenarios B and D is undefined because corner case $m_1 = 0$ implies division by zero (eq. A.22 and A.28). To address such issues, we reformulate the household's problem for each case, and solve it using the same above-described methods.

$\mathbf{m_1 = m_2 = 0}$ **and** $\mathbf{m_3 > 0}$

Here the household is an outright owner of a house that is fully financed with the endowment A_0. There is no optimization in this setting as only one life stage exists, during which the household

[32] To avoid computational indeterminacy in cases where $R = a_1$ or $V = a_2$, or $V = a_3$, we add 0.1 to the argument of the *log* function: $U_t = \log C_t + \theta_t \log \left(V_t^H - a_t + 0.1\right) \equiv \log C_t + \theta_t \log 0.1$.

is a hand-to-mouth consumer, hence the solution is trivial:

$$C_3 = I_3, \qquad V = A_0.$$

$\mathbf{m_2 = m_3 = 0}$ and $\mathbf{m_1 > 0}$

In this corner case, the household lives in a rental house throughout its whole lifetime. The problem boils down to a simple maximization of $U_1(C_1, R)$ utility with respect to C_1 and R, subject to budget constraint $A_0 g + z(I_1 - C_1 - \rho R) = 0$, resulting in the following solution:

$$C_1 = \frac{A_0 g + z(I_1 - \rho a_1)}{z(1 + \theta_1)}.$$

$\mathbf{m_2 = 0}$, $\mathbf{m_1 > 0}$, and $\mathbf{m_3 > 0}$

This is a situation where the household rents and saves for house purchase without a mortgage. Since there is no debt, scenarios are irrelevant as borrowing constraints (9)-(11) become obsolete, simplifying the optimization problem to the following:

$$\begin{aligned} U = m_1 \cdot U_1(C_1, R) + (T - m_1) \cdot \beta_3 \cdot U_3\left(I_3, V\right) \longrightarrow \max_{\{C_1, R, V, m_1\}} \\ \text{s.t.} \qquad V = A_0 g(r_A, m_1) + z(r_d, m_1)(I_1 - C_1 - \rho R). \end{aligned}$$

The solution boils down to:

$$C_1 = (A_0 g + z(I_1 - \rho a_1) - a_2)\left[\frac{z}{m_1}\Gamma_2 + z(1 + \theta_1)\right]^{-1}, \quad V = a_2 + C_1 \frac{z}{m_1}\Gamma_2,$$

$\mathbf{m_1 > 0}$, $\mathbf{m_2 > 0}$, and $\boldsymbol{\lambda} = \mathbf{1}$

The solution is not well-defined if $\lambda = 1$ under scenario A, where LTV constraint is binding and DSTI is not. The following solution accommodates this circumstance:

$$C_2 = \frac{\beta_2 m_2 (I_2 - a_2 f)}{\Gamma_2 + \beta_2 m_2}, \quad C_1 = \frac{\frac{A_0 g}{z} + I_1 - \rho a_1}{1 + \theta_1}, \quad V = \frac{I_2 - C_2}{f}.$$

$\mathbf{m_1 = 0}$ and $\mathbf{m_2 > 0}$

This special case covers the situation where a household can outright purchase a house with a mortgage without saving for the down payment. The household does not need to live in a rental home, thus the down payment is financed with the initial endowment A_0.

Here $m_3 = T - m_2$ and the optimization problem narrows down to:

$$U = m_2 \cdot \beta_2 \cdot U_2(C_2, V) + (T - m_2) \cdot \beta_3 \cdot U_3\left(I_3, V\right) \longrightarrow \max_{\{C_2, V, m_2\}}$$

s.t.

$$V = A_0 + \frac{I_2 - C_2}{f(i, m_2)}, \qquad \lambda \geq \frac{I_2 - C_2}{V f(i, m_2)}, \qquad \delta \geq \frac{I_2 - C_2}{I_2}, \qquad \mu \geq m_2.$$

In case $\lambda < 1$, the solutions under each scenario are the following:

$$\begin{aligned}
&\text{A:} \quad && C_2 = I_2 - \frac{\lambda A_0 f}{1 - \lambda}, && V = \frac{A_0}{1 - \lambda}, \\
&\text{B:} \quad && C_2 = (1 - \delta) I_2, && V = A_0 + \frac{\delta I_2}{f}, \\
&\text{C:} \quad && C_2 = (1 - \delta) I_2, && V = \frac{\delta I_2}{\lambda f}, \\
&\text{D:} \quad && C_2 = \left[f(A_0 - a_2) + I_2\right]\left[1 + \frac{\Gamma_2}{\beta_2 m}\right]^{-1}, && V = a_2 + C_2 \frac{\Gamma_2}{\beta_2 m_2 f}.
\end{aligned}$$

A well-defined solution for scenario C necessitates an additional condition, requiring sufficient endowment for the down payment:

$$A_0 \geq \frac{\delta I_2 (1 - \lambda)}{f \lambda}.$$

In case $\lambda = 1$:

$$\begin{aligned}
&\text{A:} \quad && \frac{\beta_2 \left(\frac{A_0 z}{m_2} + m_2(I_2 - f a_2)\right)}{m_2 \beta_2 + \Gamma_2}, && V = \frac{A_0 z}{m_2^2 f} + \frac{I_2 - C_2}{f}, \\
&\text{B:} \quad && C_2 = (1 - \delta) I_2, && V = A_0 + \frac{\delta I_2}{f}, \\
&\text{C:} \quad && C_2 = \frac{A_0 z}{m_2^2} + I_2(1 - \delta), && V = \frac{\delta I_2}{f}, \\
&\text{D:} \quad && C_2 = \left[f(A_0 - a_2) + I_2\right]\left[1 + \frac{\Gamma_2}{\beta_2 m}\right]^{-1}, && V = a_2 + C_2 \frac{\Gamma_2}{\beta_2 m_2 f}.
\end{aligned}$$

A.5 Simulating Multiple Heterogeneous Households

Here we describe how household parameters Θ_h are randomly simulated from the $B(\Xi|Z_t)$ distribution, using the basic version of the model presented in Section 2 and applied in Section 3.1. We assume a vector of 24 hyperparameters: $\Xi := (\xi_1, \dots, \xi_{24})$. Then, h-household-specific model parameters Θ_h are generated recursively according to the following system:

$$
\begin{array}{lll}
T \sim \text{MatDistr}(\xi_1, \xi_2), & & \\
\theta_2 \sim \text{Gamma}(\xi_3, \xi_4), & \theta_3 \sim \text{Gamma}(\xi_5, \xi_6), & \theta_1 = \theta_2, \\
\beta_1 = 1, & \beta_2 \sim \text{Uniform}(\xi_7, \xi_7 + \xi_8), & \beta_3 \sim \text{Uniform}(\xi_9, \xi_9 + \xi_{10}), \\
I_1 = \max\left\{0; \xi_{11} Z_t^{(1)} + \varepsilon_I\right\}, & \varepsilon_I \sim \text{Normal}(\xi_{12}, \xi_{13}), & I = I_2 = I_3 = I_1 \\
A_0 = \max\{0; I\varepsilon_A\}, & \varepsilon_A \sim \text{Normal}(\xi_{14}, \xi_{15}), & \\
\rho = \max\left\{0; \xi_{16} Z_t^{(2)} + \varepsilon_\rho\right\}, & \varepsilon_\rho \sim \text{Normal}(\xi_{17}, \xi_{18}), & \\
a_1 = \max\left\{0; \xi_{19} Z_t^{(3)} + \varepsilon_{a_1}\right\}, & \varepsilon_{a_1} \sim \text{Normal}(\xi_{20}, \xi_{21}), & \\
a_2 = \max\left\{0; \xi_{22} Z_t^{(3)} + \varepsilon_{a_2}\right\}, & \varepsilon_{a_2} \sim \text{Normal}(\xi_{23}, \xi_{24}), & \\
r_A = 0, & r_d = 0, & i \sim \text{Beta}\left(Z_t^{(4)}, Z_t^{(5)}\right).
\end{array}
$$

MatDistr(ξ_1, ξ_2) is a custom distribution function for generating household lifespan durations. Its domain is defined as $T \in \{20, 25, 30, 35, 40\}$, with respective probabilities $p = \{p_0, p_0\xi_2, p_0\xi_2^2, p_0\xi_2^3, \xi_1\}$, with $p_0 := \frac{(1-\xi_1)(1-\xi_2)}{1-\xi_2^4}$. $\theta_1 = \theta_2$ is assumed for simplicity. Note that relaxing this assumption did not change the model results.

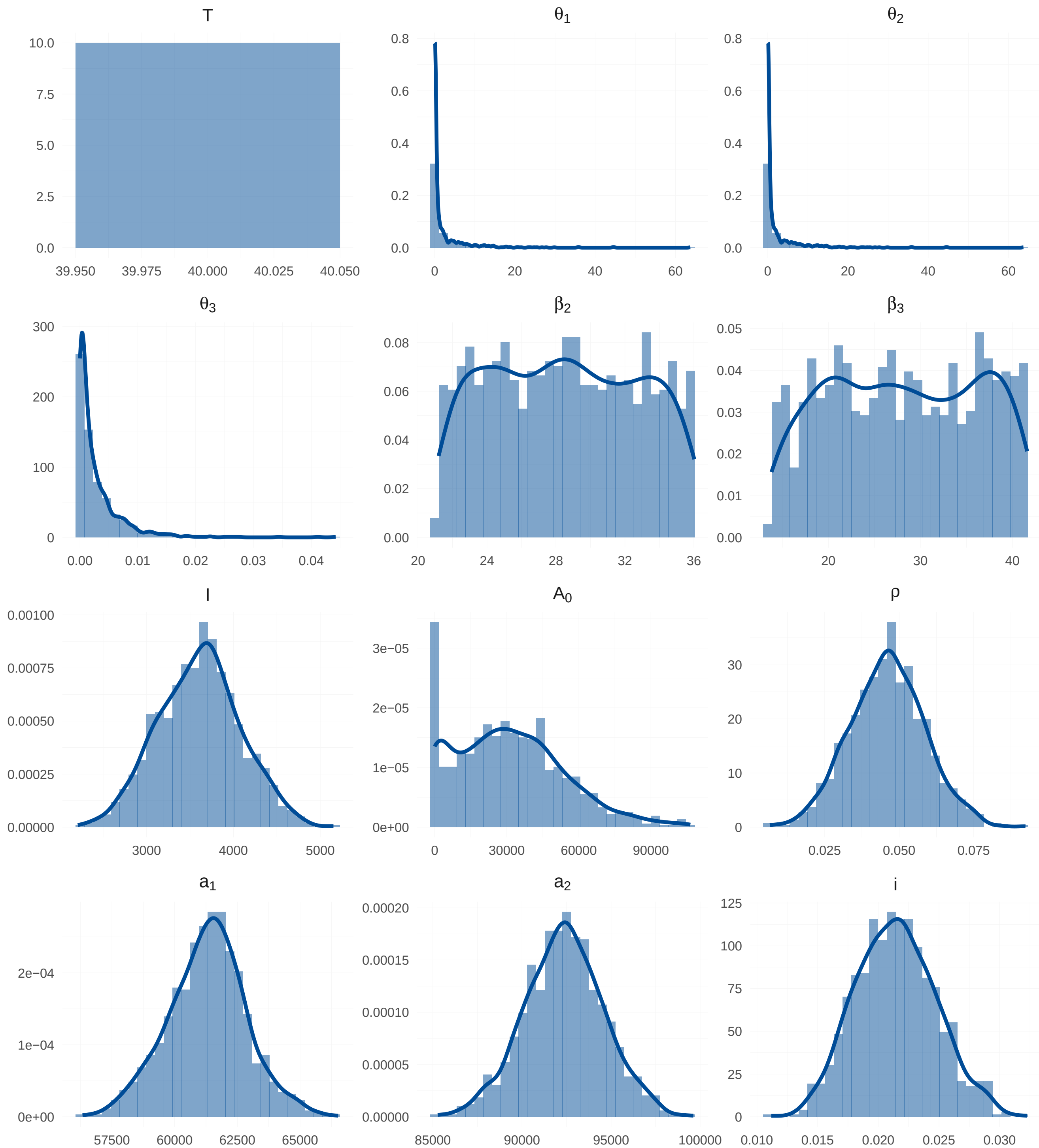
Macroeconomic variables vector $Z_t = \left(Z_t^{(1)}, Z_t^{(2)}, \dots, Z_t^{(5)}\right)$ contains time series values of: (1) household disposable income, (2) rental price ratio to house price index, (3) house price index, (4) interest rate distribution shape parameter, and (5) scale parameter. The latter two parameters are obtained by pointwise fitting the interest rate distribution of actual loan data over time.

Table A.8 contains Lithuania's hyperparameter estimates, which are used to simulate model parameters, whose distributions are depicted in Figure A.18.

Table A.8: Hyperparameter Estimates $\hat{\Xi}$: Lithuania

ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	ξ_8	ξ_9	ξ_{10}	ξ_{11}	ξ_{12}
350.94	117.24	0.16	0.08	0.51	174.70	21.19	14.85	13.81	27.86	8.01	7.00
ξ_{13}	ξ_{14}	ξ_{15}	ξ_{16}	ξ_{17}	ξ_{18}	ξ_{19}	ξ_{20}	ξ_{21}	ξ_{22}	ξ_{23}	ξ_{24}
2338.44	1.22	462.73	0.01	3.96	0.01	7020.18	455.02	1541.03	1570.34	760.49	2231.14

Figure A.18: Simulated Parameters Θ_h: Lithuania



Notes: Simulations of $\Theta_h \sim B(\Xi|Z_t)$ parameters for 1,000 households, based on Table A.8 estimates, and Lithuanian data for 2017Q1. The bars represent a relative frequency histogram, and lines mark the nonparametric density function.

Appendix B Additional Tables and Figures for Slovakia

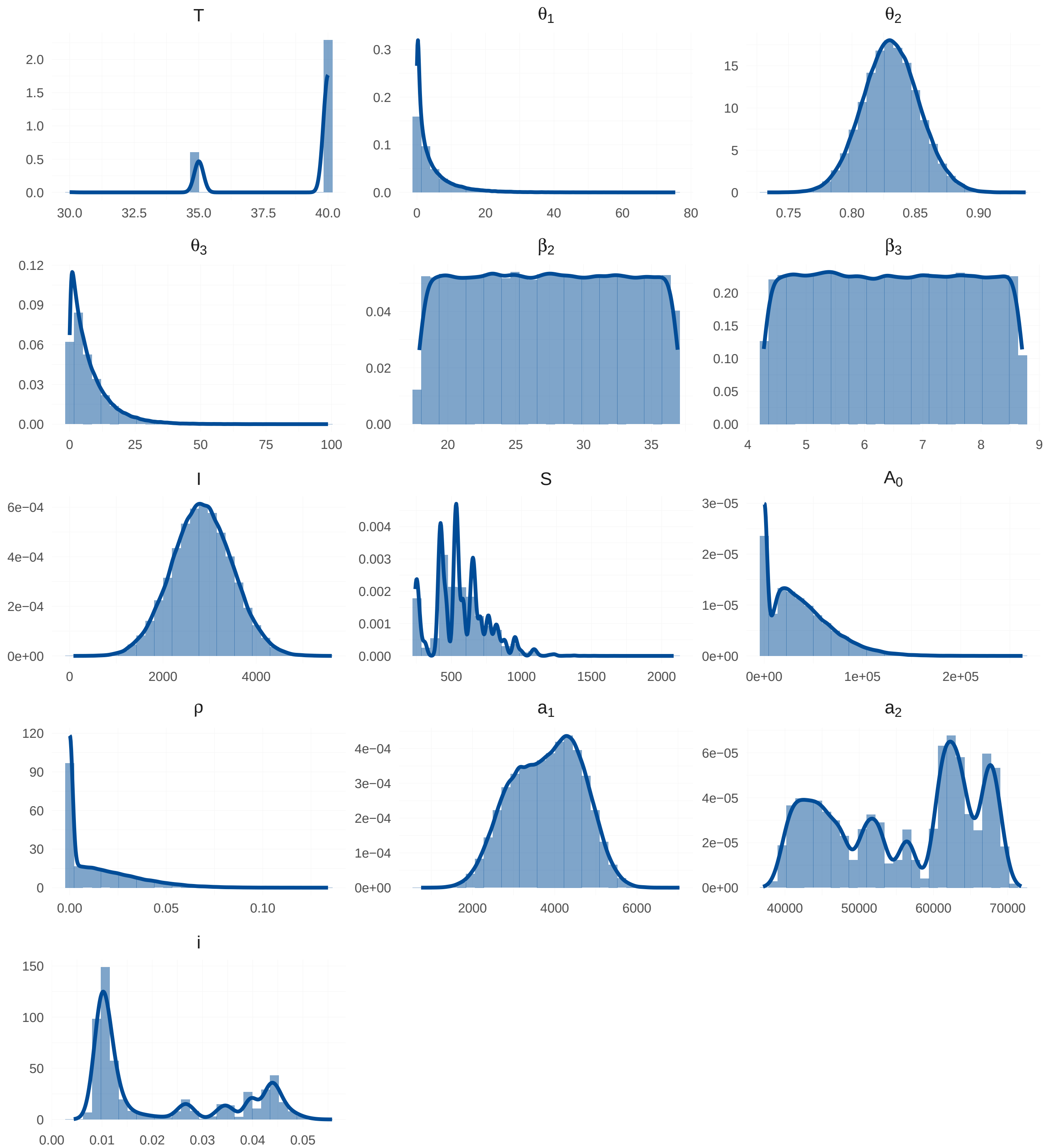
Table B.1: BBM Speed Limits in Slovakia

	LTV (λ)		DSTI (δ)		Maturity (μ)		DTI (κ)	
Date	Limit (%)	Share (%)	Limit (%)	Share (%)	Limit (%)	Share (%)	Limit (%)	Share (%)
2018 Q4	90	30	80	100	40	10	15	15
2018 Q4	80	70	-	-	30	90	8	85
2019 Q4	90	20	80	100	40	10	15	10
2019 Q4	80	80	-	-	30	90	8	90
2020 Q4	90	20	70	5	40	10	15	10
2020 Q4	80	80	60	95	30	90	8	90
2021 Q4	90	20	70	5	40	10	15	10
2021 Q4	80	80	60	95	30	90	8	90
2022 Q4	90	20	70	5	40	10	15	10
2022 Q4	80	80	60	95	30	90	8	90
2023 Q4	90	20	70	5	40	10	15	10
2023 Q4	80	80	60	95	30	90	8	61.65
2023 Q4	-	-	-	-	-	-	6.875	22.81
2023 Q4	-	-	-	-	-	-	4.25	5.19
2023 Q4	-	-	-	-	-	-	3	0.30

Table B.2: Hyperparameter Estimates $\hat{\Xi}$: Slovakia

ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	ξ_8	ξ_9	ξ_{10}	ξ_{11}	ξ_{12}
0.79	138.37	0.54	0.13	1397.31	1682.13	0.96	0.13	17.89	19.03	4.27	4.43
ξ_{13}	ξ_{14}	ξ_{15}	ξ_{16}	ξ_{17}	ξ_{18}	ξ_{19}	ξ_{20}	ξ_{21}	ξ_{22}	ξ_{23}	ξ_{24}
6.79	14.32	613.85	1.51	628.36	-0.01	1.51	0.03	-583.76	24.09	474.28	-4778.29

Figure B.1: Simulated Parameters Θ_h: Slovakia



Notes: Simulations of $\Theta_h \sim B\left(\Xi|Z_t\right)$ parameters for 1,000 households, based on Table B.2 estimates, and Slovak data from 2020Q1. The bars represent a relative frequency histogram, and lines mark the nonparametric density function.

PUBLICATIONS

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