IMF Working Paper

Stress Testing and Calibration of Macroprudential Policy Tools

by Lucyna Górnicka and Laura Valderrama

INTERNATIONAL MONETARY FUND

WP/20/165

IMF Working Paper

Monetary and Capital Markets Department

Stress Testing and Calibration of Macroprudential Policy Tools*

Prepared by Lucyna Górnicka and Laura Valderrama

Authorized for distribution by Martin Čihák

August 2020

Abstract

We present a semi-structural model of default risk, which is a function of loan and borrower characteristics, economic conditions, and the regulatory environment. We use this model to simulate bank credit losses for stress-testing purposes and to calibrate borrower-based macroprudential tools. The proposed approach is very flexible and is particularly useful when there is limited history of crisis episodes, when crises bring unanticipated shocks where past tail events offer little guidance and when structural shocks or changes in financial regulations have altered the loan default process. We apply the model to quantify mortgage lending risk in two distinct mortgage markets. For each application, we show a range of modeling adjustments that can be made to capture country-specific institutional features. The model uses bank portfolio data broken down by risk bucket and vintage, which enables us to take explicit account of the loan life cycle and to incorporate the housing and economic cycles. This feature facilitates a timely assessment of banks' loss-absorbing capacity and the buildup of systemic risk conditional on policy. It also enables counterfactual analysis and the evaluation of macroprudential policy interventions.

TABLE OF CONTENTS

APPENDICES

I. INTRODUCTION

The consensus that has emerged after the global financial crisis is that macroprudential policies can help strengthen the resilience of the financial system by leaning against the buildup of financial vulnerabilities. As a result of this consensus, new macroprudential tools have been added to policymakers' toolkits. Notwithstanding the guidance introduced by the Bank of International Settlements (BIS) in 2012 and the International Monetary Fund (IMF) in 2014[1], there is no broad agreement on the definition of the macroprudential policy stance, the way that macroprudential tools should be calibrated, and which scenarios are more relevant to project systemic risk. This debate carries over to the adequacy and effectiveness of different policy instruments. Finally, there is still little clarity on what constitutes a timely execution of macroprudential policies, despite this being one of the most important operational considerations.

Our paper has two main objectives. The first one is to provide a conceptual framework of systemic risk and risk resilience to support the discussion on macroprudential policy measures. Previous work has shown that a conceptual framework is needed to shed light on the notion of macroprudential stance (ESRB 2018, Bank of England 2020). We propose a way to operationalize the financial stability objective by defining a policy goal that is linked to readily available metrics. This in turn enables a straightforward assessment of success of macroprudential instruments in enhancing financial system resilience. More specifically, we characterize the setting of macroprudential policy as minimizing a loss function that would erode a significant fraction of banking system capital conditional on the realization of a distribution of risk factors, where we benchmark projected stressed credit losses against peak nonperforming loans (NPLs) during a systemic banking crisis based on Laeven and Valencia (2018).

Our second objective is to apply the framework to the mortgage loan markets in two different countries that have been active in addressing risks in the real estate sector. Here our approach allows for an assessment of the appropriateness of the macroprudential policy stance and for quantification of the necessary adjustment in the calibration of macroprudential instruments. While the modeling approach can be used for other loan types, we focus on the real estate market, given the importance of mortgage loan portfolios (including both retail and corporate loans secured by immovable property) in banks' balance sheets. This implies that the materialization of mortgage credit risk can have a substantial impact on banks' solvency position, which in turn can impair financial intermediation. Moreover, as mortgages are frequently the largest liabilities of households, severe distress can also affect the real economy through a reduction in aggregate consumption.

---

[1] See BIS (2012), IMF (2014).

This paper contributes to the macroprudential policy debate in four ways. First, it proposes a stress testing approach based on a semi-structural model of mortgage default to provide a forward-looking measure of a banking system's resilience. This approach can be seen as an attractive alternative to purely empirical techniques in the presence of structural shifts or changes in regulation, lack of past distress episodes, or unavailability of sufficiently long time series. Second, it shows how the approach can guide the calibration of macroprudential policy tools through a counterfactual analysis. Third, it shows how the conditional distribution of GDP growth (that is, growth at risk) can inform the design of a tail risk scenario used (in the semi-structural model) to calibrate macroprudential policy tools. Finally, the paper takes into account the lag between policy implementation and the realization of tail events to gauge the effectiveness of macroprudential policies.

While stress tests are increasingly used as a tool to ensure that the banking system has sufficient capital buffers to be able to withstand future adverse shocks, the precise way in which stress test results can be used to inform macroprudential policy is rarely explored. Similarly, whereas many jurisdictions have adopted macroprudential measures to address financial stability risks, the quantification of the expected effects that adoption of macroprudential policies can have on mitigating systemic risk remains a challenge[2]. Often, authorities apply a guided discretion approach in the calibration of macroprudential policy to provide the necessary flexibility given the inherent uncertainty and the lack of experience associated with operating macroprudential instruments. This paper aims to bridge the gap between stress testing and macroprudential policy by presenting a flexible semi-structural modeling approach of bank losses that can be used to guide macroprudential policy decisions[3].

Regulatory Data and Drivers of Mortgage Risk

One of the key obstacles for bank stress-testing and for the calibration of macroprudential instruments is the availability of sufficiently granular data. While micro-level data are becoming frequently available in many countries, they often lack sufficient information on mortgage characteristics or are not updated frequently enough. For example, the Eurosystem's household finance and consumption survey (HFCS) covers 20 countries, but it is only available since 2013 and only at a three-year frequency, and it does not include

---

[2] For instance, Article 458 under the European Capital Requirements Regulation (CRR) requires member states to submit relevant evidence of the changes in the level of systemic risk, the reasons such charges could pose a threat to financial stability, and an explanation as to why the draft macroprudential measures are deemed suitable, effective, and proportionate to address the situation, but the evidence tends to be qualitative or based on intermediate indicators.

[3] While a similar approach was implemented in the 2020 Canada FSAP (IMF 2020b) to project mortgage defaults in Canada, the model was not used to inform macroprudential policy. Some of the previous studies have attempted to assess the efficacy of macroprudential tools in reducing household mortgage loss rates using stress test-based simulation techniques (Gross and Población 2017) or econometric approaches (Nier et al. 2019), but they have abstracted from detailed considerations of macroprudential instruments calibration.

information on loan performance.[4] As a result, the latest micro-level data at hand tend to be backward-looking and often do not properly reflect the risk profile of the outstanding stock of loans at a given point in time. Additionally, and more importantly, even if the access to micro-level data was broad and timely, one would need to map individual loan and borrower characteristics to the distribution of obligor grades in banks' loan portfolios to assess the impact of default risk on bank resilience.

This paper takes a more practical approach that allows us to overcome the abovementioned hurdles. Instead of relying on micro-level borrower data, it uses data on banks' portfolio characteristics. This type of data is usually more readily available to the regulators, as it is frequently submitted in regulatory reporting templates. The use of regulatory reporting data facilitates policy evaluation, as it is segmented according to the same risk buckets as those used by regulators to monitor vulnerabilities. In the proposed semi-structural model, the assessment of credit risk is done through simulations of default rates and expected losses by risk-vintage buckets of loans at the individual bank or at the systemwide banking sector level. Within each loan bucket, a set of triggers under which an individual borrower defaults is first defined, and then default rates and loan losses are simulated for each risk bucket under a prespecified tail risk scenario.

The selection of fundamental drivers follows the literature on mortgage affordability risk and includes (1) state variables (debt, income, collateral value); (2) shocks, which are classified as either idiosyncratic (demographic shocks or unemployment shocks) or systematic (income shocks, shocks to real estate, interest rate shocks); and (3) parameters (transaction costs, foreclosure discount, risk premia). Affordability risk is also determined by the mortgage payment schedule, which depends on the characteristics of housing finance, including the type of mortgage, its repricing schedule, and its tenor.

Crucially, by simulating losses for risk-vintage buckets, we can control for latent variables related to the life cycle of loans. For instance, a loan-to-value (LTV) ratio of a mortgage will decrease over time as borrowers pay down their loan and as the value of real estate increases. This also allows us to control for changes to lending standards through the housing and economic cycle. For example, an LTV of 80 percent on mortgages issued when house prices are undervalued will be significantly tighter than when house prices are overvalued and subject to a price correction. Similarly, a debt-service-to-income ratio (DSTI) limit of 40 percent will be conservative when interest rates are high, but lax in a low interest rate environment. The proposed model is sufficiently flexible to incorporate also the adjustments to the regulatory framework, which can affect the size of the loan and the schedule of amortization and interest payments across loan vintages.

---

[4] The new PSD performance data (PSD007) mortgage requirements were introduced in 2015, but the data had to be reported for all live regulated mortgage contracts, including those opened before 2015.

We consider two broad types of macroprudential policies that can be used to strengthen banks' resilience to real estate losses. The first one is bank capital requirements that can absorb loan losses under stress, for example, through the activation of sectoral capital buffers for mortgage lending. The second one is to tighten underwriting standards by applying borrower-based tools, such as caps on LTVs, limits on DSTIs, or more stringent amortization requirements.

Developments in the Swiss and Austrian mortgage market

Housing markets across countries differ in many ways. We conduct the policy analysis in two distinct housing markets (Switzerland and Austria) to provide insights into critical drivers of mortgage risk and to demonstrate the flexibility of the model to accommodate different policy measures. In both countries macroprudential policy authorities have taken actions to tackle elevated risks in real estate from increased lending volumes and high prices, and amid concerns over the sustainability of lending standards. At the same time, while Switzerland and Austria share some similarities in their housing markets, including low homeownership ratios and well-developed rental markets, they are quite different in many aspects[5].

Switzerland experienced in the 1980s a real estate bubble, which burst in the early 1990s. This stress episode facilitates the calibration of model parameters and enables the backtesting of our model. At the same time, the activation of binding macroprudential policies starting in 2012 has changed the structure of the mortgage market. Thus, when we apply the model to the Swiss case, we show how it can be enhanced to account for changes in regulations with a differential impact on default risk across loan vintages. We then use the model to investigate whether the size of the sectoral countercyclical capital buffer (CCyB), first introduced in 2013 and reassessed in 2014, is sufficient to make the banking sector resilient to an adverse stress scenario, and to investigate—through a counterfactual analysis—the sensitivity of stressed bank losses to changes in binding amortization requirements.

By contrast, Austria has never experienced a sharp house price correction, but there is evidence of increasing real estate overvaluations in recent years. The share of variable-rate loans in Austria is quite high—making debt servicing costs sensitive to increases in lending rates. At the same time, the typical maturity of loans is long (between 25 and 30 years), contrary to Switzerland where loans tend to have short tenors (from two to 10 years) and are typically rolled over. In 2017, the Austrian authorities added a set of borrower-based tools to the macroprudential toolkit, including LTV, DSTI, and DTI (debt-to-income) limits, though those tools have not yet been activated. In September 2018, the Austrian authorities published a guide on sustainable lending standards in real estate financing to prevent further buildup of systemic risk. When we apply the model to the Austrian real estate market, we

---

[5] Schneider and Wagner (2015) analyze various aspects of the housing and mortgage markets in Austria, Switzerland, and Germany to explain why their house price developments deviated from other European countries.

conduct forward-looking simulations of portfolio losses under stress in order to assess the effectiveness of different calibrations of the borrower-based macroprudential policy instruments, should they be activated.

The rest of the paper is structured as follows: Section II presents the conceptual approach to measure the macroprudential policy stance. Section III introduces the baseline model of borrower default, building on Harrison and Mathew (2008). Section IV applies an enhanced version of the model to bank stress testing in Switzerland. Section V presents how the model can be used to calibrate macroprudential (borrower-based) policy tools using the example of the Austrian housing market. In the respective sections, we show how the baseline model can be adjusted to capture country-specific characteristics of the housing market and the regulatory environment. Section VI concludes.

II. LOSS MODELING FRAMEWORK

To help focus the analysis, we present a conceptual framework of systemic risk and risk resilience. We first define the scenario under which systemic risk is projected. Then we benchmark our expected credit losses against a relevant loss metric. To be able to define the macroprudential policy stance, we then assess the extent to which current macroprudential instruments can absorb systemic risk, or increase the resilience of outstanding bank mortgage portfolios. When stress test results point at the deterioration in the credit risk profile of new mortgages, we propose a rule to guide changes in macroprudential policy as to minimize the loss function of new mortgage production relative to a benchmark portfolio.

We use two alternative approaches to formulate the stress test scenario. The first approach is consistent with a systematic procedure that searches for the distribution of risk factors that yields the worst expected value of the portfolio, conditional on plausibility of this event materializing. The general formulation is based on Breuer and Summer (2018). The approach searches for the worst expected value of the portfolio valuation function among the sufficiently plausible generalized scenarios:

$$\sup_{\Omega : D(\Omega \| \Psi) \leq K} E_{t,\tau,\Omega}(X_T)$$

where Ω is a risk factor distribution of key drivers of portfolio losses relative to the historical distribution Ψ, $E_{t,\Omega,\tau}(X_T)$ is the expectation at time t of the amount of cumulative losses X on the loan portfolio at time T under current macroprudential policy τ conditional on the distribution Ω. The function $D(\Omega \| \Psi)$ represents the distance between distributions Ω and Ψ, and provides a measure of plausibility relative to historical experience. Rather than using the measure of relative entropy like in Breuer and Summer (2018), we use a dynamic stochastic general equilibrium (DSGE) approach to determine the plausibility between historical outcomes and the set of plausible distributions.

The second approach is to use the conditional distribution of growth at risk (GaR) and house price at risk (HaR) to inform the design of the risk scenario Ω. This approach, pioneered by Adrian et al. (2019), relies on statistical techniques to project the conditional distribution of future GDP growth and real estate prices as a function of current economic and financial conditions. This methodology focuses on probabilities and is more adequate when the focus of macroprudential policy is on projecting systemic risk conditional on the *current* (most recent) distribution of risk factors and the macroprudential policy stance.

To judge whether the current risk environment is elevated, we need to benchmark our projected losses against some loss distribution. This is shown in the specification below

$$E_{t,\tau,\Omega}\left(X_T\right) \geq L_C$$

where L is the level of losses observed during a relevant crisis episode C, for instance, the global financial crisis, or a severe real estate price downturn in the country at hand, or in a peer benchmark country.

To inform the policy stance assessment, the level of systemic risk measured by $E_{t,\tau,\Omega}\left(X_T\right)$ is compared against the existing resilience of the banking sector, to come up with a measure of "net systemic risk." This comparison allows inferring whether an adjustment to the calibration of macroprudential policy is required by either reducing the level of systemic risk ($E_{t,\Omega,\tau}\left(X_T\right)$) or by enhancing a banking system's resilience (K_t):[6]

$$E_{t,\tau,\Omega}\left(X_T\right) - K_t > \beta_t$$

where the LSH of the inequality denotes the amount of net systemic risk under current macroprudential buffers K_t and β_t parameterizes the risk tolerance of policymakers. This assessment is discussed in detail in the empirical application of Section IV. If the inequality holds, the macroprudential policy stance is non-neutral, and future policy action can be considered to tighten the stance. The parameter β_t is defined by the policy preferences of the macroprudential authority, related, for example, to the duration of stress, the volatility of policy intervention, or the cost of tightening to avoid severely restricting lending to the real economy.

Once the decision to tighten macroprudential policy has been taken, policy action depends on the available macroprudential instruments in the policy toolkit. Countries that have introduced the CCyB buffer can increase the CCyB rate to reduce net systemic risk (equivalent to increasing K_t in the equation above). Countries with borrower-based tools (for example, DSTI, LTV limits) can introduce caps on these instruments (equivalent to reducing

---

[6] This is in line with the framework for the assessment of the macroprudential stance proposed by the European Banking Authority (2018).

$E_{t,\Omega,\tau}\left(X_T\right)$). Note that, in contrast with the CCyB buffer, which applies to the outstanding portfolio, the implementation of borrower-based limits is confined to the production of new loans. Thus, to operationalize the calibration of borrower-based tools, the policymaker needs to quantify the riskiness of the new loan production against a reference portfolio, as shown in the following function:

$$\min_{B,p,\lambda} \left| E_{t,B,\Omega}\left(X_T^{new}\right) - E_{t,\Omega}\left(X_T^{ref}\right)\right|$$

$$s.t. \Pr\left(B\left(L_t^{new}\right) > p\right) \leq \lambda$$

Where B is a borrower-based tool, L_t^{new} the production of new mortgages at time t, p is the p-th quantile of the B distribution, and λ the probability level $\lambda \in [0,1]$ that the new loans will exceed the cap implemented by the authorities. This level will be set to zero if "hard" limits are introduced, or to a small value if the so-called "speed limits"[7] are allowed instead. This assessment is presented in more detail in the empirical application in Section V.

III.   BASELINE MODEL OF BORROWER DEFAULT

The concept underlying the way we model credit risk is the "ability to pay" principle, where factors affecting a borrower's capacity to service his or her payment obligations are identified as the main predictors of a default. Such factors exhibit a significant relationship with financial distress and are usually grouped into three categories[8]:

- *macroeconomic conditions*, which include changes in the path of interest rates, aggregate income, and real estate valuations;

- *loan characteristics*, that is, the type, tenor, rollover rate, and size of the loan relative to its collateral value; and

- *borrower characteristics*, which include idiosyncratic events related to the borrower's income (for example, caused by a rise in unemployment), and demographic shocks (for example, changes in the composition of the household).

In this paper we also consider a fourth category—which has become more important over time with more frequent use of regulatory measures related to real estate lending—that allows us to analyze the impact of macroprudential policies on systemic risk:

---

[7] An LTV limit of 80 percent with a speed limit of 10 percent means that a maximum of 10 percent of new loans can have an LTV of more than 80 percent. A hard limit of 80 percent means that no new loans with LTV of above 80 percent can be granted.

[8] This categorization is similar to the one underpinning the assessment of mortgage affordability risk by the Financial Conduct Authority in its efforts to support the mortgage market review in the UK (FCA 2015).

- *changes in the regulatory environment*, defined by adjustments to binding minimum standards such as the minimum down payment, affordability caps, and the maximum amortization requirements for mortgage loans.

To quantify credit risk, we apply a set of conditions under which an individual borrower defaults conditional on the drivers outlined above, and then simulate bank losses on the loan portfolio under a pre-specified tail risk scenario. The default conditions reflect the case of collateralized (mortgage) loans, but they can be easily adjusted if unsecured loans are considered instead.

A. Mortgage Default

The modeling approach used to define the default event follows Harrison and Mathew (2008). They specify two conditions that need to be satisfied for a borrower to default on a collateralized loan. The first condition is that the borrower is in financial distress, unable to service the loan on time due to liquidity constraints. The probability that a borrower i gets into financial distress in period t is

$$\Pr\left(FD_{i,t}\right) = \Phi\left(DSTI_{i,t-1}\right) \cdot D_i + \beta_1 \cdot \Delta DSTI_{i,t-1}{}^{\gamma} + \Phi\left(DSTI_{i,t-1}\right) \cdot \left(\beta_2 \cdot U_{t-1} + \beta_3 \cdot \Delta U_{t-1}^{\alpha}\right). \tag{1}$$

It is a function of (1) a borrower's debt servicing capacity ($\Delta DSTI$), measured by the debt service-to-income ratio ($DSTI$) in the previous period; (2) the change in the debt servicing capacity since the last period; (3) the likelihood of being unemployed measured by the unemployment rate (U) in the previous period; (4) the increase in the unemployment rate since the last period (ΔU); and (5) a demographic factor (D). While the baseline specification does not account explicitly for the stock of financial assets, a sensitivity analysis in Section V shows how the effect of financial assets on mortgage default risk can be incorporated in the model.

Intuitively, debt servicing capacity deteriorates (and DSTI increases) when the borrower's income goes down or when the loan is repriced at a higher rate (which depends on the type of the loan and the repricing frequency). Similarly, a higher unemployment rate increases the likelihood of becoming unemployed and thus losing a stable source of income[9]. The demographic factor D captures a range of idiosyncratic variables (for example, the change in the size of the household or financial mismanagement) that could cause financial distress. For simplicity, the incidence of these idiosyncratic events is assumed to be independent of changes in the interest rate and the unemployment rate.

---

[9] In a fully micro-level model, equation (1) could be replaced by a condition for a distressed sale, with the dependent variable taking the value of 1 if the borrower remains unemployed for some time or the DSTI increases above a certain threshold. This threshold could be borrower-specific, reflecting the size of the household and employment of other household members, available savings, and so on.

Changes to the DSTI ratio and the unemployment rate in equation (1) can have a non-linear impact on the probability of financial distress, as reflected by parameter γ[10].

We also assume that the effect of idiosyncratic shocks (that is, related to demographic and other factors not captured by the model explicitly) is non-linear in the initial DSTI ratio. This is captured by the function $\Phi\left(DSTI_{i,t-1}\right)$ whereby idiosyncratic shocks have no impact on financial distress below a certain DSTI threshold. However, once the threshold is passed, the function increases gradually until an upper threshold is reached where the effect has full impact. Section III.C explains the calibration of parameters in equation (1) in more detail. As credit quality indicators such as LTV ratios, credit scores, and risk ratings vary by vintage, the financial distress equation is estimated by vintage and risk bucket. The probability of default of the outstanding portfolio is calculated by combining separately simulated outputs for vintage-risk buckets and weighting them by the share in the total portfolio.

In the event of financial distress, an early termination of the mortgage by selling the underlying collateral at current market price may be the only option to avoid default. Taking this strategy into account is supported by the empirical literature on negative equity and foreclosure[11]. To reflect this possibility, we assume that the default occurs when the borrower is in distress *and* cannot repay the loan to the bank early by selling the collateral at market price $\tilde{P}$ net of transaction costs C[12]:

$$\tilde{P}_{i,t} - C < NPV\left(L_{i,t}, r_t^{type,M}, r_t^f, T_{s,t}\right) \qquad (2)$$

In contrast with Harrison and Mathew (2008), the net present value of the loan at time t consists of two elements: (1) the outstanding loan amount, $L_{i,t}$; and (2) the penalty for early prepayment, which is assumed to equal the net present value of future interest payments. The reference point for the computation of the interest payments is the outstanding value of the loan at time t:

$$NPV\left(L_{i,t}, r_t^{type,M}, r_t^f, T_s\right) = L_{i,t} + \sum_{j=0}^{T-1} \frac{r_t^{type,M} L_{i,t}\left(1 - \dfrac{j}{T_{s,t}}\right)}{\left(1+r_t^f\right)^j} \qquad (3)$$

---

[10] The Financial Conduct Authority (2015) study finds that the *slope* of the probability of impairment (as a function of DSTI) is higher for DSTI ratios between 0 and 25 percent than for higher DSTI ratios. It also estimates that a quarter of the most affluent households and two-thirds of low-income households have total net expenditure exceeding net income—evidence of financial overstretch to meet their mortgage payments. For these borrowers, a large income shock will push them into default, as non-essential expenditure cannot be adjusted in a timely manner.

[11] Foote et al. (2009) find that, contrary to popular belief, negative equity is a necessary but not a sufficient condition for foreclosure during the real estate crisis of the early 1990s in the US.

[12] The transaction cost is likely to increase during a crisis, given the high stock of foreclosed properties.

where $r_t^{type,M}$ stands for the current interest rate of a mortgage conditional on its type (fixed or floating) and maturity (M), $T_{s,t}$ stands for the remaining maturity at time t of a loan issued at time s, and r_t^f is a risk-free rate used to discount the value of future interest payments. The amortization schedule (for each period j over its remaining lifetime) is proxied by a linear amortization scheme. This implies that the amortization rate in a given period is given by $\frac{L_{i,t}}{T_{st}}$; see Appendix I for details.

The inclusion of the net present value of future interest payments in condition (2) reflects the fact that withdrawing from a contract ahead of the original mortgage term normally involves paying a penalty fee for breaking the contract. National rules determine whether a bank can ask a borrower to pay compensation for early termination. This compensation, if applicable, is bounded by the financial loss to the lender—which is proxied by the amount of foregone interest payments over the remaining life of the mortgage discounted at the risk-free rate. Therefore, the penalty typically depends on the mortgage interest rate and the remaining mortgage term, as in equation (3). Naturally, the model can be adjusted to reflect other ways of computing the early repayment fee[13].

Conditional on defaulting, a bank's loss on a mortgage is driven by the discounted sale price of the collateral. The loss given default (LGD) is calculated assuming that the sale occurs at time $t+n$ (where n denotes time needed to repossess the collateral and to sell the property) and that the sale proceeds after applying a discount to the foreclosed asset δ are discounted at a rate reflecting the risk premium of the foreclosed asset[14] ($spread$). As the market price of the collateral typically changes between the default date and the sale transaction date, the applicable price is the expected value at time $t+n$, i.e., $\tilde{P}_{i,t+n}$.

The LGD equation reflects the fact that civil law or other relevant regulations stipulate that if the selling price exceeds the outstanding claim, the difference has to go back to the borrower:

$$LGD_{i,t} = \max\left(0, NPV(L_{i,t}, r_t^{type,M}, r_t^f, T_{s,t}) - (1-\delta) \times \frac{\tilde{P}_{i,t+n}}{\left(1+r_t^f+spread\right)^n}\right) \quad (4)$$

From the perspective of standard indicators of affordability risk, the model focuses on two key metrics of mortgage default and bank loan losses: the DSTI ratio—which affects the probability of financial distress in equation (1)—and the LTV ratio—which affects the ability of the borrower to prepay the loan by selling the collateral reflected in condition (2) as well as bank losses upon default in equation (4)[15]. In the case of Switzerland, changes to the

---

[13] For instance, the penalty for early prepayment in Belgium is three months of foregone interest. In France, charges are computed as a percentage of the face value of the loan, while in the US, there is no penalty for early termination of the contract. In the latter case, equation (2) would simplify to $\tilde{P}_{i,t} - C < L_{i,t}$.

[14] Given the uncertainty involved in the payment proceeds from the sale of the foreclosed property, the bank discounts the expected value at a rate higher than the risk-free rate.

[15] In Section IV, the LTV ratio also enters the default equation (1), as Swiss banks have the right to request a margin call from the mortgagor to comply with amortization rules.

current LTV value also affect financial distress by tightening the debt service ratio through the activation of margin calls. Section IV provides details.

If only one of the conditions (1)–(2) is satisfied, there is no default event. If the borrower can afford to service the loan, he or she will do so even if the value of the real estate property falls below the outstanding balance on the mortgage. Likewise, if the borrower cannot afford to service the loan but the house is worth more than the loan value, the borrower will sell the house to repay the outstanding debt and move to another property or to a rental accommodation. This is a rational decision, as the borrower can extract value for his positive home equity.

It is worth mentioning that the model does not consider the so-called "strategic defaults," that is, a situation where the borrower decides to stop repayments once the value of the underlying collateral falls below the outstanding value of the loan. Incentives to do so might exist in the case of non-recourse loans, that is, when a lender has no claim on the borrower's possessions (or income) other than the underlying collateral. The non-recourse loans are common, for example, in several states in the US, while full-recourse loans dominate in most European markets. However, even in the case of the US, Elul et al. (2010) document that many borrowers with negative equity do not default. Instead, they show that illiquidity, in addition to negative equity, is a strong predictor of mortgage default. Bhutta et al. (2010) find that the US median borrower does not default until equity falls to -62 percent of the home value, and Foote et al. (2009) find that fewer than 10 percent of owners with negative equity in the early 1990s in the US eventually defaulted. In any case, default conditions (1)–(2) can be easily changed to reflect country-specific characteristics. For example, Gross and Tereanu (2019) consider only illiquidity shocks as the driver of default, similar in vein to the financial distress requirement in equation (1).

Finally, while our definition of default does not explicitly allow financially distressed borrowers to draw on their savings in order to continue mortgage repayments (unlike Gross and Población 2017), equations (1)–(4) can be easily augmented to account directly for borrowers' financial assets. For example, in the sensitivity analysis in Section V, we consider the impact of Austrian households' financial assets on the cumulative mortgage losses by reformulating equation (2).

B. Scenario Construction and Parameter Calibration

Scenario construction

The model quantifies credit risk by considering loan default and loan loss rates during a period of adverse macroeconomic conditions. Such an "adverse scenario" defines forward paths for key variables driving loan losses: borrowers' income, unemployment rate, interest rates, and house prices. The scenario is assumed to last over two or three years, which is motivated by the observation that adverse economic shocks take time to materialize and

trigger defaults in the loan portfolio[16]. In Section IV, the forward path for macrofinancial variables is generated by a DSGE model over the forecasting period. In Section V, we design the adverse scenario to match the current (cyclical) estimate of downside risks, using a GaR and HaR approach (Adrian et al. 2019). Changes to macroeconomic variables based on the outputs of the "at-risk" models reflect the peak-to-trough dynamics during the simulation period.

In general, the severity of the macroeconomic scenario depends on the purpose of the exercise. In bank-level stress testing it is common to consider adverse conditions significantly more severe than during typical business-cycle downturns. When we apply the model to bank stress testing in Section IV, the adverse scenario is designed to apply stresses that are sufficiently severe but plausible given the risk exposure of Swiss banks. This is to ensure that the stress test provides a meaningful assessment of banking system resilience[17]. Instead, when we calibrate borrower-based macroprudential policies in Section V, we design the adverse scenario to reflect the current (cyclical) assessment of downside risks to provide a notion of likelihood. The purpose is to link the calibration of macroprudential tools to the current level of risks to macro-financial stability[18].

Parameter calibration

Parameters in equations (1)–(4) can be divided into four groups: (1) a set of parameters that define sensitivity of default rates and mortgage losses to a change in macroeconomic drivers (unemployment, mortgage lending rates, house prices); (2) the parameters that reflect characteristics of housing loans and the structure of the housing market; (3) the parameters calibrated to match current or past levels of banks' mortgage losses; and (4) the parameters that reflect the (macroprudential) regulatory framework.

The function $\Phi\left(DSTI_{t-1}\right)$ and parameters β_1, β_3, α and γ in equation (1) reflect the sensitivity of financial distress to changes in unemployment, DSTI, and LTV through shocks to income, unemployment, and lending rates. Their calibration is guided by the dynamics in default rates and loan losses observed in past loan distress episodes. In the baseline model, Harrison and Mathew (2008) calibrate parameters β_1, β_3, α, and γ to the *aggregate* UK housing loan loss experience in the early 1990s, when residential mortgage interest rates increased by over 3.5 percentage points, unemployment increased by 60 percent, and house prices fell by about 30 percent over a period of three years. During the same period, the stock of mortgage arrears

---

[16] The model-generated cumulative loss rate over the forecasting period is divided by the number of years to obtain the one-year expected loss rate.

[17] This is in line with the BIS guiding principles for stress testing (BIS 2018).

[18] Ultimately, the severity of the scenario should be linked to the risk appetite of the prudential authorities too.

of six months or more increased by a maximum of 600 percent, and loan write-offs increased between one hundred and two hundred times.

$\Phi\left(DSTI_{t-1}\right)$ is calibrated to reflect the *non-linear* dependence of borrowers' default on idiosyncratic shocks (driven by demographic or other changes). This is to capture the fact that the incidence of idiosyncratic events is not constant across DSTI buckets. For example, Nier et al. (2019) document that the probability of a borrower's default on mortgage increases substantially once the DSTI exceeds a threshold of 50 percent[19]. In general, we consider a functional form of the function $\Phi\left(DSTI_{t-1}\right)$ as follows:

$$\Phi(DSTI_{t-1}) = \begin{cases} 0 \; if \; DSTI_{t-1} < \; a \\ \dfrac{DSTI_{t-1} - a}{b - a} \; if \; DSTI \; \in [a, b] \\ 1 \; if \; DSTI_{t-1} > b \end{cases}$$

where *a* and *b* stand for positive values between 0 and 1. In Section IV, we show how these and other of the above parameters can be calibrated to capture the real estate crisis in Switzerland in the early 1990s.

The second group of parameters reflects country-specific housing market characteristics. For example, in the case of mortgage loans, the cost parameter C in equation (2) can be calibrated to the average level of taxes and notary fees charged in house sale transactions. The discount parameter δ in equation (4) reflects the fact that foreclosure depresses house prices below the normal buyer price. Harrison and Mathew (2008) estimate it to be about 15 percent for New Zealand, whereas Pennington (2003) provides an estimate of about 25 percent for the US. The time needed to realize a sale of collateral underlying a defaulted loan, *n,* in equation (4) reflects the time needed for a bank to finalize legal proceedings to recover collateral and to sell it on the market. Harrison and Mathew (2008) estimate it to be 1.25 years in New Zealand.

The demographic parameters D and β_2 (the third group of parameters) are set to match the average bank loan loss rates on mortgage claims reported by banks in "normal" times. Finally, in Section IV, we allow the regulatory framework to affect the default conditions (1)–(2). In particular, changes in the required amortization schedule introduced in Switzerland in 2012 and 2014 will have differential effects on affordability risk and time to maturity $T_{s,t}$ across vintages.

---

[19] Nier et al. (2019) consider individual borrowers (and borrower-specific DSTIs) rather than households.

C. Simulation of Portfolio Losses

Mortgage probability of default (PD) and portfolio-wide LGD are generated through simulations. In practice, we divide the portfolio of mortgages into buckets based on their key characteristics and simulations are carried out for each bucket separately. We consider buckets by the year (or quarter) of mortgage origination[20], loan-to-income (LTI) bucket, and LTV bucket. Depending on the available data, simulations can be done using different bucketing (for example, DTI or DSTI ratio).

For a given vintage-LTI-LTV bucket of mortgages, a number N of borrowers *already in financial distress* is considered. For each of the N borrowers, a house price draw is generated from a distribution with a mean equal to the average house price level in the tail risk scenario. For each of the house price draws, the model determines whether condition (2) is satisfied (that is, if the borrower defaults) and—if so—the LGD is calculated from equation (4). In the next step, the bucket-specific PD is calculated as the number of cases in which the expected sales price falls short of the loan's net present value (NPV) divided by the number of draws, N, and multiplied by the bucket-specific probability of financial distress from equation (1):

$$PD_{i,t} = \frac{\sum_{i=1}^{N} I\left(\tilde{P}_{i,t} - C < NPV\left(L_{i,t}, r_t^{type,M}, r_t^f, T_{s,t}\right)\right)}{N} \times \Pr\left(FD_{i,t}\right) \quad (5)$$

where $I\left(\tilde{P}_{i,t} - C < NPV\left(L_{i,t}, r_t^{type,M}, r_t^f, T_{s,t}\right)\right)$ is an indicator function equal to 1 if condition (2) is satisfied. The bucket-specific LGD is computed as the average of LGDs among defaulted loans.

To ensure that simulation results converge, this simulation process is then repeated K times for each bucket b. The final bucket-specific PDs and LGDs are calculated as the averages across K iterations. In the applications presented in sections IV and V, we set $N=2000$ and $K=10,000$.

In the final step, the ultimate outputs—the portfolio-wide PD, LGD, and the loss rate (portfolio PD times the portfolio LGD)—are calculated by combining separately estimated outputs for the vintage-LTI-LTV buckets and weighting them by the share in the total portfolio. Results are highly non-linear across vintage-LTI-LTV buckets, as illustrated in Figure 3, for the application to the Swiss mortgage market.

As explained above, to simulate portfolio losses, we use risk bucket-specific probability of financial distress at the bank or banking sector level, instead of the borrower-specific

---

[20] The vintage of the mortgage matters, as it allows us to calculate the impact of interest shocks on affordability risk, the remaining time to maturity, and the market value of collateral and thus the point-in-time (PiT)-to-LVT ratio. Based on this information, we can calculate the outstanding size of the loan in period t and its NPV in equation (3).

probability introduced in equation (1). That is, we replace the borrower-specific values of DSTI in (1) with the average DSTI in a given vintage-LTI-LTV bucket. Naturally, it is a simplification, and the use of micro data at the borrower- and loan-level would allow us to capture a broader range of borrower and loan characteristics that matter for the default decision[21]. At the same time, individual borrower- and loan-level data are often not easily available, especially at the desired frequency. For example, although many countries conduct large-scale consumer or household surveys, this is usually done once every few years. Often, data quality issues arise because surveys are not a part of regulatory reporting, and surveys are not always representative of the entire market. Additionally, given the low frequency of surveys, the last available survey might not be representative of the current population of borrowers[22]. Finally, even if surveys were collected at a higher frequency, the risk profile of the population may not be representative of banks' outstanding lending portfolios.

Instead, supervisors have increasingly regular access to information on risk-bucket LTVs, LTIs (and DTIs) through regulatory reporting of banks, which can be updated even at quarterly frequency. This increases the attractiveness of the model proposed in this paper for supervisory purposes. Additionally, empirical evidence (for example, Lazarov and Hinterschweiger 2018) confirms that LTV and DSTI ratios are the main drivers of borrower distress, particularly in the owner-occupied segment.

IV. STRESS TESTING AND CHANGES TO MACROPRUDENTIAL REGULATION IN SWITZERLAND

This section applies the structural mortgage risk model to the housing market in Switzerland. In the past few years, developments in the mortgage and real estate markets in Switzerland have attracted increasing attention. In August 2019, the Swiss Bankers Association (SBA) tightened rules for mortgage lending for investment properties following the Swiss Financial Market Supervisory Authority (FINMA) assessment that "the signs of overheating in investment property could only be dealt with effectively by making changes to macroprudential policy tools[23]." Swiss financial market supervisors and macroprudential authorities have been concerned about the risks to the financial sector deriving from the mortgage market for some time due to the environment of high real estate prices, strong loan growth, and low interest rates. Switzerland also has been active in the implementation of macroprudential policy measures since 2012.

---

[21] See Jurca et al. (2019), Lazarov and Hinterschweiger (2018), and Gross and Población (2017).

[22] This matters as, in general, recently originated mortgages are found to be the major driver of aggregate losses on mortgage portfolios in bank stress tests.

[23] FINMA (2019a, 2019b).

A. Mortgage Market in Switzerland

The mortgage and real estate markets have been a major concern for financial stability in Switzerland over the past few years. Strong growth in real estate prices has resulted in imbalances on the residential real estate market, with an estimated accumulated growth rate of 50 percent in the investment-led segment and 75 percent for owner-occupied property over 1999–2018 (Figure 1). Conversely, there are signs of increased affordability risk, with the share of new mortgages where imputed costs would exceed one-third of income at an interest rate of 5 percent at about 50 percent. In addition, Swiss banks are heavily exposed to mortgage loans. About three quarters of Swiss banks' lending portfolio (at the parent level) are mortgage loans. This share increases for domestically focused banks (DFBs), reaching 95 percent for Raiffeisen and regional and savings banks, and 87 percent for cantonal banks.

Figure 1. Bank Mortgage Portfolio and Real Estate Prices in Switzerland

Note: Loan exposure data for Swiss banks and the real estate price index in Switzerland are sourced from SNB statistics. The real estate price index is shown by sub-segment including owner-occupied (housing), investment-led (inv_led), and commercial real estate (CRE).
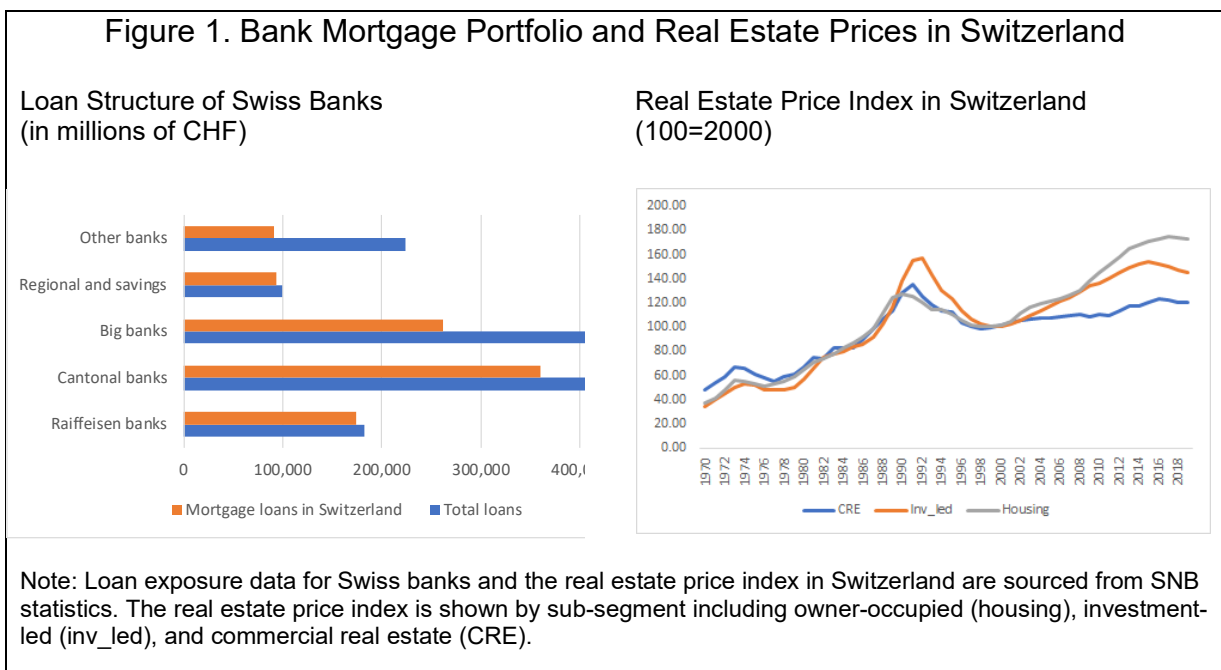
The limited data from actual tail events in Switzerland, presence of structural changes in the mortgage market, and adjustments to the regulatory framework make the semi-structural statistical model presented in Section III an attractive alternative to approaches that project mortgage loss rates based only on regressions of past loan performance on macrofinancial variables. Statistical approaches are also hindered by the current benign cycle, with aggregate loss rates on mortgage claims at about 10 basis points over the past three years, leading to low starting portfolio PDs.

B. Regulatory Framework

Switzerland became the first country to activate the Basel macroprudential sectoral CCyB in February 2013. The CCyB was applied to the entire domestic residential mortgage book, that is, the stock of existing mortgages on the bank's balance sheet as well as all new mortgages.

The initial calibration was set at 1 percent of these risk-weighted assets. The sectoral CCyB was reset at 2 percent of risk-weighted assets in 2014.[24]

There are three additional changes to the Swiss regulatory framework that have impacted the availability and riskiness of mortgage lending. First, the structure of the mortgage market changed markedly in 1995, when Swiss residents were allowed to draw on their second- and third-pillar pension assets to fund part of their mortgage downpayment. Second, on July 1, 2012, FINMA declared the SBA's self-regulation a new minimum standard applicable to all banks. This brought about two major adjustments to the regulatory framework. First, the LTV ratio on new mortgages had to be reduced to at most two-thirds within at most 20 years[25]. Second, homebuyers were required to provide at least 10 percent of the house value as "hard equity," that is, own funds excluding pension assets. Finally, in June 2014, the SBA adjusted its self-regulation regime, shortening the maximum amortization period from 20 to 15 years. While there are no quantitative caps on LTV, it is typically below 80 percent in the owner-occupied segment.

There are two other characteristics of the current regulatory environment in Switzerland that matter for evaluating the mortgage credit risk. Under the current tax system, Swiss borrowers benefit from taking leverage, and therefore most of the mortgages are not amortized fully. Thus, each mortgage can be divided into the "first mortgage" and the "second mortgage." The first mortgage covers up to two-thirds of the underlying property value and does not need to be amortized, that is, it is an interest-only mortgage. If the borrower needs a bigger loan, he or she will have to take out a second mortgage. Unlike the first mortgage, the second mortgage must be amortized within the maximum period required by regulation.

Also, Swiss banks have the option to request a *margin call* if the value of the collateral, after a housing price correction, is insufficient to meet self-regulation rules. While the bank can ask for a margin call immediately (the cancellation period is six months), the individual situation of the borrower, the value of the collateral, and market conditions are likely to feed into the bank's decision. Since margin calls are not always desirable from a systemic risk perspective, as they may generate amplification effects through fire sales, there is no hard-wired or automatically triggered execution mechanism.

In subsection D, we discuss in detail how we capture Swiss regulatory rules in the model. Overall, the debt service ratio in equation (1) will be a function of both interest payments and the amortization schedule. We also allow the amortization schedule to be different for loans originated in different years to account for changes in binding minimum standards. Additionally, we allow the DSTI to increase not only due to higher interest rates, but also as a result of "margin call" activation. We assume that a margin call is triggered when the

---

[24] As a reaction to the Covid pandemic, the sectoral CCyB in Switzerland has been reduced to 0 percent in March 2020.

[25] Effectively, this implies that the value of the loan in excess of two-thirds of the value of collateral needs to be amortized within a maximum of 20 years.

decline in the value of the collateral leads to a violation of the amortization requirement and is satisfied within the remaining duration of the contracts.

C. Defining the Stress Scenario

We perform our stress test on 12 major Swiss banks that represent over 80 percent of the banking system's total assets: two large internationally active banks, six DFBs, and four private banks; at a reference date of 2018[26]. We generate a severe macroeconomic scenario over five years, 2019–23. While the model produces default rates over the first two years of stress, 2019–20, we need a longer horizon to generate forward paths for real estate prices to estimate the market value of the collateral that is repossessed and sold by banks after foreclosures. The scenario is triggered by a global financial cycle downturn with abrupt and sizeable repricing of risk premia in global financial markets generating a housing price correction in Switzerland. The scenario is calibrated using the IMF's in-house Global Macrofinancial Model (GFM)[27].

Table 1. Key Macroeconomic Assumptions in the Stress Scenario for Switzerland		
Variable	Cumulative Percentage Change over Two Years (Baseline)	Cumulative Percentage Change over Two Years (Adverse)
Real disposable income	3.6%	-4.4%
Real house price level	0%	-25.4%
Unemployment rate	-0.11%	1.4%
Mortgage rate	1.25%	3.75%

Note: The table shows the cumulative changes in key macroeconomic variables that affect mortgage default and losses. The paths are projected using a DSGE model with exogenous shocks. The scenario implies a deviation of real GDP from its baseline level by 7.7 percent in 2020, with a 3.3 standard deviation move in two-year cumulative real GDP growth rate.

Macrofinancial stress triggers a recession in Switzerland, with GDP growth in negative territory for seven quarters and a peak decline of -4.75 percent in 2019. The scenario implies a deviation of real GDP from its baseline level by 7.7 percent in 2020, with a 3.3 standard deviation move in two-year cumulative real GDP growth rate. We project a cumulative 25.4 percent peak-to-trough decline in real estate prices during 2018–20, with a differentiated impact across mortgage segments and a further 8.6 percent price correction by 2023 (Figure 2). The severity of the adverse macro-financial scenario lies within the range of severities explored by the SNB in its financial stability reports' adverse scenarios for stress testing.

---

[26] See IMF (2019) for a full description of the scenario and the stress test.

[27] See Vitek, F. (2018), "The Global Macrofinancial Model," IMF Working Paper 81.

Figure 2. Stress Test Scenario Paths for Real Estate Prices in Switzerland
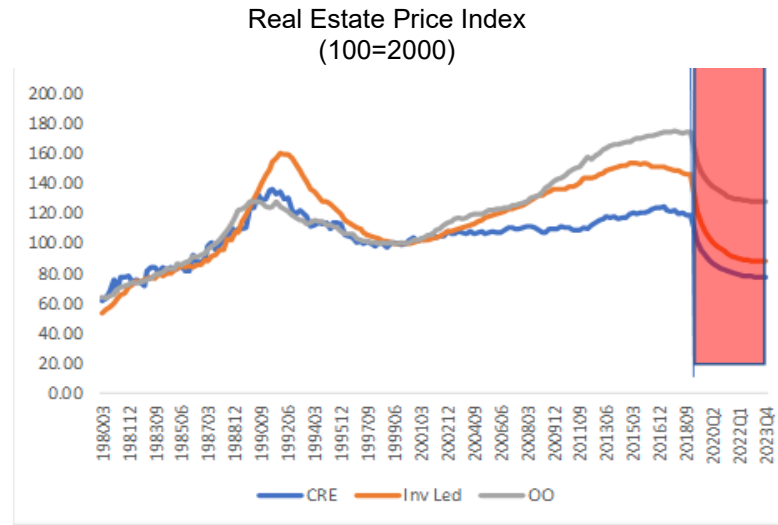
Note: This figure plots real estate price paths by sub-segment, including owner-occupied (OO), investment-led (inv_led), and commercial real estate (CRE), under the adverse scenario assumptions generated by the DSGE model shown in Table 1.

We apply the scenario inputs to the structural model of default. Annualized rates for probabilities of default are generated by solving the following equation:

$$PD_t^{cum} = PD_t + (1 - PD_t) \cdot PD_t$$
$$PD_t = 1 - \sqrt{2 - 2 \cdot PD_t^{cum}}$$

Key scenario assumptions are shown in Table 1.

D. Model inputs

We use supervisory bank-level data on the distribution of mortgages across risk buckets at end-2018 from FINMA's Building Block Analysis (BBA) templates for the large Swiss banks. This distribution is applied to the remaining banks of the sample. In practice, data are reported as a matrix of outstanding mortgages by LTV and loan-to-income (LTI) ratios. A caveat of the analysis is that we use supervisory data for residential mortgages (owner-occupied and investment-led) and apply the data to the entire portfolio of loans backed by real estate. This is due to concerns over data quality of the commercial real estate sub-mortgage segment. A mitigating factor is that the real estate-backed loan portfolio is dominated by the residential mortgage sub-segment at about 80 percent (of which 50 percent is owner occupied), with commercial real estate loans accounting for 20 percent only[28].

---

[28] Thus, when we construct house price series, we consider an index reflecting this composition.

In Switzerland, banks offer three broad types of mortgage loans: fixed-rate mortgages, money-market mortgages, and adjustable-rate redeemable mortgages. In contrast to fixed-rate mortgages, the interest rate on the latter two types can change during the life of the mortgage. Fixed-rate loans are by far the most common. Currently, at least three-quarters of the outstanding mortgage volume falls into this category. The share of money-market mortgages, mostly linked to CHF libor rates, is estimated at about 15 percent, although they are more popular for recent vintages due to the low levels of money-market rates. The remaining 10 percent are redeemable mortgages with adjustable rates. The repricing schedule ranges from three months to six months to 12 months. We pool the money-market and redeemable mortgages together and label them as floating-rate mortgages. For simplicity, we assume that repricing schedule is tied to the one-year CHF libor rate.

In terms of remaining maturity—denoted by $T_{s,t}$ in equations (2)–(4)—we control for the binding amortization rules at origination. For mortgages issued after June 2014, the loan is amortized to two-thirds of the value of the collateral at origination over a maximum 15-year period. Between 2012 and the revision in 2014, the second mortgage is amortized within a maximum of 20 years. We assume that mortgages issued before 2012 also follow the 20-year amortization rule.

To assess the effect of interest rate shocks on borrowers' debt servicing capacity, we segment the bank mortgage portfolio by vintage. This matters as the impact of interest rate shocks differs across vintages. Within each segment, we capture the share of fixed- or floating-rate mortgages, the repricing schedule (for floating-rate mortgages), and the rollover rate (for fixed-rate mortgages). Rollover mortgages, in which the outstanding principal must be refinanced every few years at current interest rates, are quite popular in Switzerland. To calculate the rollover date, we assume that at maturity, each mortgage is rolled over to match the maturity of the original contract at prevailing market rates in order to comply with the self-regulation rules. The number of rollover periods, therefore, depends on the origination year and on the initial maturity of the mortgage[29].

Drawing on SNB statistics, we assume that 75 percent of mortgages are issued at a fixed rate, with maturities ranging between one and 10 years. For each vintage and tenor, we construct a matrix of repricing schedules. We apply the new lending rate to the contracts that are rolled over during the two-year stress testing period. To compute the average rollover rate and the repricing rate of each vintage, we assume a fat tail distribution supported on the bounded interval of maturities between one and 10, and apply the repricing matrix weighted by the share of tenors in the portfolio. The remaining 25 percent of mortgages are issued at floating rate linked to one-year CHF libor. The stressed market interest rate is applied to all non-maturing floating-rate mortgages, as loans are assumed to reprice annually.

---

[29] The average maturity is about five years for fixed-rate mortgages and three years for floating-rate mortgages.

We account for the margin call as follows. We recalculate the LTV during the stress testing period for each simulated loan (that is, for each draw, we obtain a house price realization). If the initial amortization rate falls short of repaying the outstanding loan in excess of two-thirds of the current value of the collateral over the remaining maturity, the bank applies a margin call to satisfy the amortization rule, tightening the amortization schedule. Otherwise, the initial amortization schedule applies.

We illustrate the structural features of the Swiss mortgage market with the following example. Consider a mortgage loan with tenor M granted to borrower i in year s for an amount $L_{i,s} = L_{i,s}^{first} + L_{i,s}^{second}$ where $L_{i,s}^{first}$ denotes the first mortgage (non-amortizing), and $L_{i,s}^{second}$ represents the second one (amortizing mortgage). The property is valued at $P_{i,s}$ and $A_{i,s}$ is the amortization rate. Therefore,

$$L_{i,s}^{first} = \frac{2}{3} P_{i,s}$$

$$L_{i,s,t} = L_{i,s,t-1} - A_{i,s} \quad \forall s < t \leq s + T_s$$

The second mortgage needs to be amortized by T_{s+j} with j linked to the amortization requirement. The value of DSTI at origination is defined as follows:

$$DSTI_{i,s,t}^{type,M} = \frac{A_{i,s} + I_{i,s,t}^{type,M}}{Income_{i,s,t}}$$

where A stands for amortization of the principal, $I_{i,s,t}^{type,M}$ for interest payments that depend on the mortgage type, and *Income* is the borrower's income. The mortgage amortization schedule depends on the regulatory rule at issuance. Assuming a linear schedule[30], a mortgage issued at time s is subject to the following amortization schedule:

$$A_{i,s} = \frac{L_{i,s}^{second}}{T_{s,s}} \quad where \quad T_{s,s} = \begin{cases} 20 & if \ s < 2014 \\ 15 & if \ s \geq 2014 \end{cases}$$

During the lifetime of the mortgage, credit risk is managed by reassessing the value of the collateral against the outstanding principal. This requires computing the point-in-time (PiT)-to- LTV ratio for the *outstanding* amount of the loan (that is, the LTV of a mortgage as of end-2018 in the case of Switzerland). A *margin call* is triggered if the maximum amortization rule cannot be satisfied over the remaining duration of the mortgage (including

---

[30] Current self-regulation rules stipulate a linear repayment schedule. Before the revision in 2014, self-regulation rules did not constrain the repayment schedule to be linear.

the rollover period). The amortization schedule is then updated each period according to the rule below:

$$A_{i,s,t}^{mc} = \max \left(\frac{L_{i,s,t} - \frac{2}{3} P_{i,t}}{T_{s,t}}, \frac{L_{i,s} - \frac{2}{3} \cdot P_{i,s}}{T_{s,s}} \right)$$

This specification illustrates that while a margin call protects the lender against credit default risk, it may increase the likelihood of default by tightening the amortization rule, particularly for stretched borrowers. Under a scenario in which lending rates increase at the same time as real estate prices collapse, the margin call can act as an amplification conduit of shocks[31]. Interest payments are linked to the type of mortgage and the current macroeconomic environment. For a fixed-rate mortgage that is rolled over every M years, interest payments are calculated on the outstanding balance of the loan at the market rate prevailing in the last repricing date as follows:

$$I_{i,s,t}^{fixed,M} = r_{s,t}^{fixed,M} \cdot L_{i,s,t}$$
$$r_{s,t}^{fixed,M} = R_{s+floor\left(\frac{t-s}{M}\right) \cdot M}^{fixed,M}$$

where $floor\left(\frac{t-s}{M}\right)$ is a floor function that captures the repricing schedule over the life of the mortgage contract. The market rate is $R_t^{fixed,M}$ for a fixed-rate mortgage and $R_t^{floating,M}$ for a floating-rate mortgage, which is repriced every year based on the one-year CHF libor rate.

For a floating-rate mortgage, also rolled over every M years, interest payments are linked to the outstanding mortgage at the rollover rate and to the one-year CHF lending rate repriced each year as follows:

$$I_{i,s,t}^{floating,M} = R_t^{floating,M} \cdot L_{i.s,t}$$

E. Vintage Analysis

A limitation of supervisory data in Switzerland is that it does not include vintage disclosure. Instead, mortgage data are in the form of mortgage *stocks* as of end-2018. Therefore, to conduct our analysis, we need to reconstruct the vintages of mortgage flows. Given the 20-year amortization rule for pre-2014 mortgages, we focus on reconstructing vintages of 1999–2018. We approximate vintage flows using the following procedure.

---

[31] Importantly, this is the case even if the model does not allow for strategic defaults of borrowers with negative equity. Therefore, the correlation observed in the literature between negative equity and default rates is compatible with a mortgage market with full-recourse mortgages, in which margin calls can be exercised by lenders. This factor, however, has been neglected in the literature on credit risk.

First, we compute the average inflow rate and the growth of the portfolio drawing on Swiss National Bank (SNB) data to back out the stock at time t-1. Applying the inflow rate for each period gives us the volume of new mortgages issued in past vintages. Second, we compute the outstanding balance of each vintage at end-2018. To this end, we split the initial mortgage into first mortgage (interest payments only) and second mortgage (fully amortized). As this breakdown depends on LTV at origination, and this information is missing, we proceed as follows. First, we assume that a share α of the loan is the first mortgage and the remaining share of the loan (1- α) is the second mortgage. Second, we apply the amortization rule at origination to the second mortgage. Finally, we back out the value of α by matching the *calculated* outstanding stock of mortgages from each vintage (applying the regulatory amortization schedule) to the *reported* outstanding stock in 2018[32].

We then distribute the LTV share by vintage. The dataset shows the PiT distribution of LTV by bucket in the *stock* of mortgages. To calculate the LTV-vintage distribution, we consider two different approaches. Our baseline approach is to assume the same distribution of PiT LTV for each vintage. Given that older vintages have been subject to higher amortization, mortgages in high LTV buckets are more likely to be originated in recent vintages.

To test the robustness of our results to assumptions regarding LTV distributions across vintages, we rerun the model using an alternative specification that assumes the same distribution of LTV shares at origination (rather than PiT). This is a more conservative assumption in terms of resulting losses. The reason is that this procedure generates higher PiT-to-LTV ratios in recent vintages, which are riskier, given the life cycle of the loan and the recent economic and housing cycle developments (that is, lower lending rates and rising real estate valuations). See Appendix II for details.

Once we segment the portfolio by LTV-vintage buckets, the model calculates PDs, LGDs, and expected loss rates under the stress scenario specified in subsection C. Outputs for a given bank portfolio are calculated by combining separately estimated outputs for each risk bucket and weighting them by their share in the bank's outstanding portfolio.

F. Model Calibration

The model presented in Section III is recalibrated to match the historical loan losses on mortgage claims observed during the early 1990s real estate crisis in Switzerland. During

---

[32] The caveats to this approach relate primarily to the fact that we recreate the distribution of first mortgages (interest only) and second mortgages subject to mandatory amortization using overall mortgage flows. These flows could be related to staggered refinancing periods for different tranches of a loan rather than to a rollover rate matching the original tenor of the contract. Another caveat is that the data do not include material "indirect amortization" flows, which are collected on a tax privileged Pillar 3 account pledged to the bank, but do not reduce the outstanding amount of the mortgage.

1989–91, the policy rate increased from 6.0 percent in 1989 to 7.8 percent in 1991; real estate prices fell 16.4 percent peak-to-trough; unemployment increased by 52 basis points by 1991; and the estimated loss rate of the mortgage portfolio increased from 0.53 percent to 1.03 percent (subject to some uncertainty related to underlying assumptions needed to estimate the loss rate in the mortgage portfolio).

We generate an aggregate rate of financial distress in equation (1) by dividing the average loss rate over 1990–92 by the average empirical LGD to obtain the aggregate default rate. Using the average simulated share of loans with negative equity from applying equation (2), we then back out the share of the portfolio that is in distress, that is, $\Pr(FD_{i,t})$ in equation (1). In the second step, we allocate the share of financial distress due to tightening of the DSTI and due to a rise in unemployment. These are calibrated to 80 and 20 percent, respectively, following Harrison and Mathew (2008). Using information on the rise in lending rates during the Swiss crisis period and estimating the share of interest payments in the DSTI ratio in 1989 at 75 percent, we calibrate $\Phi(DSTI_{t-1})$ and γ in equation (1).

Table 2. Model Calibration for Switzerland				
Equation (1)			Equations (2)–(4)	
Parameter	Value		Parameter	Value
$\phi(DSTI)$	$\begin{cases} 1.3 \cdot \left(\dfrac{DSTI - DSTI_{min}}{1/3 - DSTI_{min}} \right) & DSTI < 1/3 \\ 1.3 & otherwise \end{cases}$		C	10% of house value
D	0.2		Ts	[1,2,3,...,10]
β_1	4.1		rf	0.05%
γ	2		spread	2%
β_2	0.06		δ	15%
β_3	2.7 if $\Delta U_t > 0$ and 0 otherwise		Q	2
α	1		σ_P	15%

Note: This table reports the core parameter values used to project credit risk losses for the Swiss banking sector.

The sensitivity of financial distress to changes in unemployment is calibrated using information on the change in unemployment over 1989–92, and the initial rate of unemployment in 1989. This yields a value for β_3 in equation (1). We follow Harrison and Mathew (2008) and set $\alpha = 1$.

We assume that the effect of idiosyncratic factors on financial distress rises gradually starting at 0 percent for DSTI, reaching full effect when the DSTI is at one-third. This follows Swiss banks' practice in assessing the affordability of mortgages, which specifies that mortgage and

running costs should not exceed one-third of household income under long-term interest rates.

Regarding repossession and sale of foreclosed collateral, we assume a period of two years from the default date (Q) following the UK Financial Conduct Authority report (FCA 2015). Finally, we calibrate D and β_2 to match the observed loss rate of the Swiss portfolio as of end-2018. We validate the model throughout the housing cycle as explained in Section IV.H. The values of model parameters are presented in Table 2.

The modeling approach delivers highly nonlinear results for the probability of financial distress across LTI-vintage buckets (Figure 3, first chart). Likewise, it yields nonlinear results across LTV-vintage buckets for the probability of economic default (Figure 3, second chart).

Figure 3. Nonlinear Effects of Financial Distress and Negative Equity as a Function of LTI, LTV Buckets, and Vintages

Probability of Financial Distress as a Function of LTI Buckets (Percent)

Probability of Negative Equity as a Function of LTV Buckets (Percent)
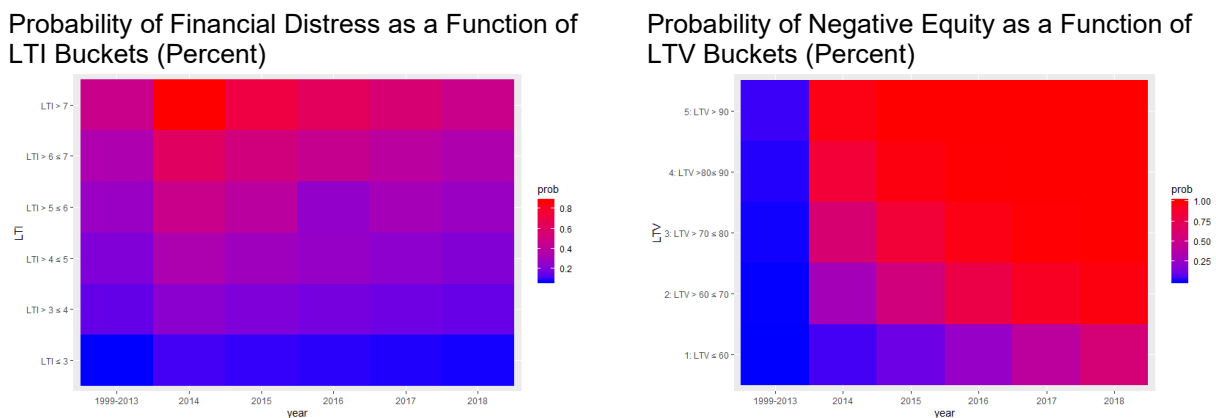
Note: This figure plots heat maps for the probability of financial distress and negative home equity. LTI is the ratio of the borrower's loan principal to his or her income at origination. LTI buckets range from lower than 3 to greater than 7. LTV is the ratio of the borrower's loan principal to the real estate collateral at origination. LTV buckets range from below 60 percent to greater than 90 percent. Red shades indicate higher probability values whereas blue shades refer to lower probability values.

For instance, the estimated probability of financial distress is higher for mortgages issued in 2014 due to the confluence of the following factors: (1) a higher share of mortgages repricing in 2019–20 relative to other vintages; (2) a higher lending rate at origination compared to recent loans; (3) a higher amortization rate relative to older vintages; and (4) a lower amortization period to satisfy a margin call. In line with intuition, older vintages tend to have lower probability of negative home equity than recent vintages.

G. Stress Test Results, Sensitivity Tests, and Robustness

Stress test results

Applying the semi-structural model to the Swiss banking system and assuming the baseline specification for the LTV-vintage distribution, the stress test results suggest that the average annualized default rate of the aggregate mortgage portfolio reaches 4.2 percent in 2019–20. The average LGD hovers around 32.3 percent. The loss rate of mortgage claims rises to 1.77 percent, leading to a 135 basis point decline of the banking system CET1 ratio. Results are depicted in Figure 4.

Based on the empirical findings by Laeven and Valencia (2018), stressed default rates at 4.2 percent point at elevated systemic risk in the real estate market. Recognizing that NPL ratios are not equivalent to default rates[33], the stressed cumulative default rate projected by our model over a two-year stress period (12.1 percent) is comparable to the median peak NPL ratio observed across systemic banking crises in advanced countries over 1970–2017 of about 13 percent, under the assumption of no write-offs or recoveries during the crisis period. The assessment of elevated risk is starker when we compare the projected default rate of 4.2 percent against the 0.55 percent default rate implied in the 1.1 percent peak NPL ratio reported by Laeven and Valencia (2018) for the Swiss banking system during the global financial crisis. In the notation of Section II, $E_{t,\tau,\Omega}\left(X_T\right) \geq L_C$, where the LHS term—at 4.2— exceeds the RHS value of 0.55 percent.

Default rates are concentrated in recent vintages with high LTV ratios. For the most recent vintages, loss rates range between 2.7 percent and 8.8 percent. By contrast, for the oldest vintages, default rates range between 0.01 percent for mortgages with LTV ratios below 60 percent and 0.14 percent for mortgages exceeding 90 percent LTV limits. These results suggest that the implementation of borrower-based measures on new vintages can be particularly effective in mitigating systemic risk. This is further explored in Section V, when the model is applied to the Austrian case.

We also project default rates in the later years of the five-year scenario (2021–23). Despite the assumed V-shape economic recovery, loss rates are material given the deterioration in borrowers' balance sheets. It is worth noting here that the proposed semi-structural approach is able to generate higher default rates than regression-based satellite models, as the latter are linked to macrofinancial developments and do not control for state variables that affect borrowers' creditworthiness[34].

---

[33] This is because NPL ratios are a function of both loan inflows from a performing status to a nonperforming status (approximated by default rates) and outflows due to recoveries and write-offs.

[34] Details of the analysis are available upon request. A similar approach is provided in IMF (2019a).

Figure 4. Stress Test Results in Switzerland

Average Annualized Projections
(Percent)

Note: This figure plots stress test results including the probability of default (PD) and the loss given default (LGD) of Swiss banks' mortgage portfolio. The data are obtained by simulating the model with the parameters shown in Table 2 under the macroeconomic assumptions reported in Table 1 for the baseline (column 1) and the adverse scenario (column 2), respectively.

Sensitivity analysis

In this section we verify the sensitivity of the stress test results to alternative assumptions about the dynamics of the two main risk factors, namely house prices and interest rates.

Real estate prices

The first test assumes the same adverse macroeconomic conditions for real disposable income and unemployment, as shown in Table 1, but a milder shock to interest rates (at a 175-basis point shift in the five-year mortgage rate to 3 percent), and considers different sizes of the decline in the real estate prices. Results suggest that the loss rate rises exponentially with the real estate price shock (Figure 5). This is explained by the nonlinear impact of collateral shocks on impairment risk as it impacts both the liquidity condition (equation 1) and the negative equity condition (equation 2). For instance, a cumulative decline in real estate prices by 40 percent by 2020 leads to an increase in loss rates to 2.3 percent and a CET1 capital depletion of 173 basis points.

Interest rates

The second test assumes the same forward paths for income, unemployment, and real estate prices as described in the adverse scenario in Table 1 but assumes a wide range of shocks to lending rates. As Figure 5 shows, the relationship between the default rates and the interest rates is exponential. This reflects the fact that shocks to interest rates enter nonlinearly into

the financial distress condition as well as into the economic default equation through the penalty for early mortgage termination.

Results suggest that the same 2.3 percent default rate can be achieved by assuming a sharp increase in lending rates to 6 percent and a moderate real estate price shock of 25.4 percent as when considering a stress scenario characterized by a softer lending rate of 3 percent but an abrupt real estate price correction of 40 percent.

Figure 5. Sensitivity Tests in Switzerland

Note: This figure plots stress test results to a wide range of shocks to underlying risk factors, that is, changes in real estate prices and stressed lending rates. The charts show the expected loss rate of the mortgage portfolio (LHS charts) and the impact on aggregate bank capital depletion (RHS charts). The data are obtained by simulating the model with the parameters shown in Table 2. The darker colored bars show the magnitude of real estate price shocks (red) and lending rate (blue) that leads to a similar loss rate and CET1 capital impact. The red line in the bottom LHS chart shows the current rate for a five-year mortgage.

Robustness

Vintage distribution assumptions

We test the robustness of our results to the distributional assumptions of LTV shares across vintages by rerunning the model using the alternative assumption described in Section IV.E.

Rather than using the baseline assumption of equal PiT LTV shares across vintages, here we assume an equal distribution of LTV shares at origination.

Given that interest rates, real estate values, and amortization rules interact nonlinearly across vintages, we expect to obtain different results. In particular, we expect the loss rate to be higher under this alternative assumption, as lending rates have been declining in Switzerland (from 3.9 percent in 1999 to 1.24 percent in 2018 for a five-year fixed-rate mortgage) and real estate prices have been increasing (by a cumulative rate of 55 percent in 1999–2018), making the most recent vintages relatively more risky.

Figure 6 confirms our hypothesis. Mortgage loss rates increase from 1.77 percent to 2.33 percent driven by a hike in PDs from 4.22 percent to 5.25 percent, adding 43 basis points to CET1 capital depletion. Interestingly, this result holds even when assuming the *same* underwriting standards at origination. This is because to match the outstanding stock of mortgages to the current PiT LTV distributions, this procedure generates higher PiT LTV ratios for more recent vintages, which are more sensitive to the peak-to-trough correction in real estate prices and the interest rate hike assumed in the scenario.

Activation of margin calls

Results are sensitive to the assumption on the activation of margin calls. Rerunning the calculations under the assumption that Swiss banks decide not to execute margin calls, the average loss rate decreases from 1.77 to 1.10 percent, leading to an increase in aggregate capital of 50 basis points.

Figure 6. Robustness Exercise: Expected Loss (EL) Rate and PD by Vintage Assumption (Percent)
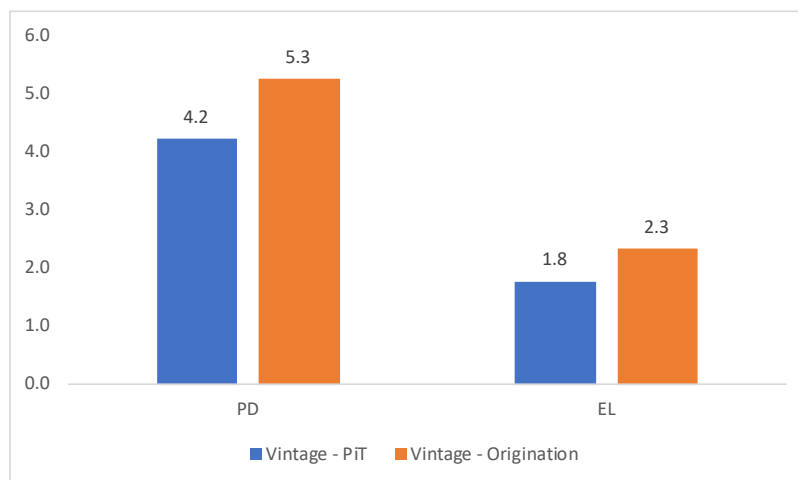
Note: This figure plots the sensitivity of stress test results to vintage analysis. The chart shows the difference in the probability of default (PD) and the expected loss rate (EL) of the mortgage portfolio under the assumption of equal point-in-time (PiT) relative LTV shares by vintage (Vintage – PiT) against the assumption of equal relative LTV shares by vintage at origination (Vintage – Origination). The data are obtained by simulating the model with the parameters shown in Table 2.

This sensitivity test illustrates the potential role played by margin calls as an amplification mechanism of financial distress. Adding second-round effects from foreclosed property selling at fire sale prices, the activation of margin calls has the potential to fuel a downward spiral of loan losses as LTVs get revalued at renewed market prices triggering a new round of margin calls.
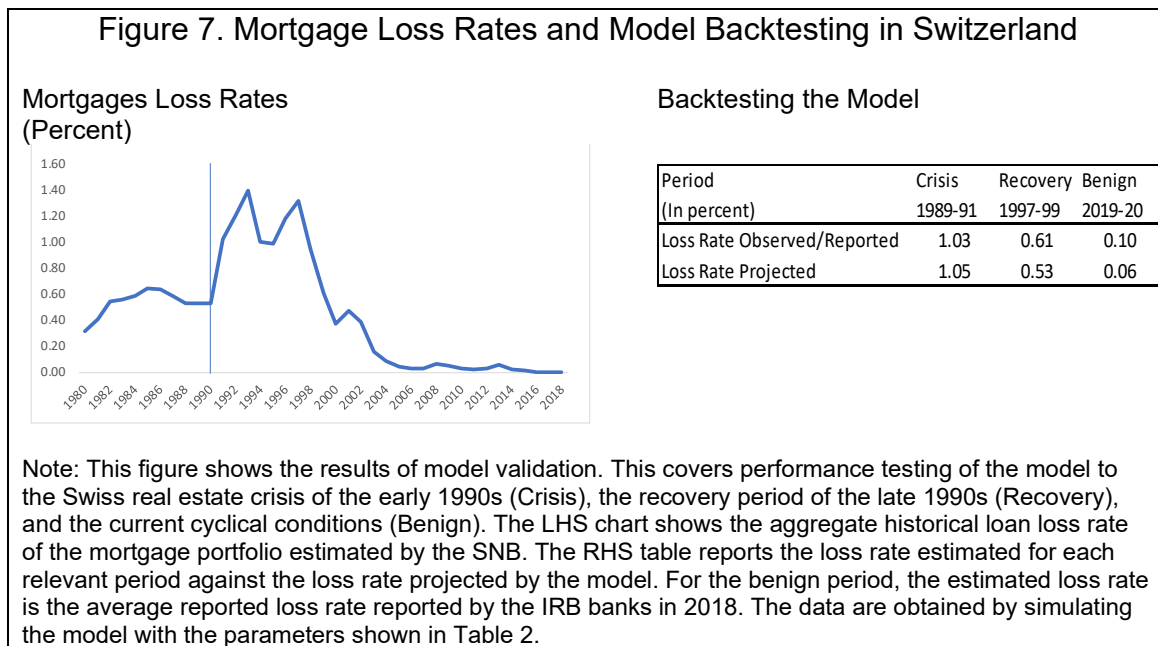
H. Model Validation

A key component to the implementation of a model-based credit risk assessment is model validation. The aim is to ensure that the model structure and parameters are chosen accurately and perform consistently under different scenario assumptions. The main metric that characterizes model quality is out-of-sample default rates. We conduct the validation exercise by discerning whether the model can replicate three major episodes: "bad times," "good times," and "benign conditions." The "bad times" scenario reproduces the Swiss housing mortgage default experience of the early 1990s. The "good times" scenario replicates the improvement in loan loss rates observed in Switzerland around 1999. Finally, the "benign conditions" simulation is captured by a baseline scenario with a gradual improvement of macroeconomic conditions over 2019–20. A caveat to this approach is that there are no data on the historical structure of banks' mortgage portfolio by LTV-vintage buckets. As explained earlier, our working assumption is that the past distribution of mortgage loans in banks' portfolios resembles the current distribution. Also, it is important to note that historical loss rates are not directly observed. Thus, we back them out by using information and judgment on the composition of overall accounting provisions.

The model is able to replicate the Swiss mortgage default event of the early 1990s, which experienced the largest relative increase in default rates. Loss rates on mortgage claims doubled in 1991 from 0.53 percent in 1989 to 1.03 percent. When the model is fed with the inputs as of 1989 and simulates the macroeconomic recession of 1991 (a 50 basis point increase in the unemployment rate to 1.1 percent, the 180 basis points increase in mortgage rates to 7.8 percent, and a peak-to-trough decline in real estate prices by 16.4 percent)[35], the projected loss rate reaches 1.05 percent, close to the observed loss rate of 1.03 percent (Figure 7).

Similarly, the model reproduces quite well the default rate observed during the late 1990s housing market recovery ("good times"). After the housing crash and the sharp increase in mortgage rates in the early 1990s, the observed loan loss rate in Switzerland halved from 1.32 percent to 0.61 percent over 1997–99. The model simulates the macroeconomic conditions prevailing in 1997 and produces a forecast for 1999 (assuming the observed decline in unemployment rate by 250 basis points to 2.7 percent, contraction in interest rates by 50 basis points to 3.9 percent, and real estate prices recovery by 1.4 percent). Again, the

---

[35] Real estate prices declined between 1992 and 1996, with a cumulative price correction of 19 percent.

simulated loss rate of 0.53 percent compares closely to the observed loan loss rate in 1999, which reached 0.61 percent (Figure 7).

Figure 7. Mortgage Loss Rates and Model Backtesting in Switzerland

Mortgages Loss Rates
(Percent)

Backtesting the Model

Period	Crisis	Recovery	Benign
(In percent)	1989-91	1997-99	2019-20
Loss Rate Observed/Reported	1.03	0.61	0.10
Loss Rate Projected	1.05	0.53	0.06

Note: This figure shows the results of model validation. This covers performance testing of the model to the Swiss real estate crisis of the early 1990s (Crisis), the recovery period of the late 1990s (Recovery), and the current cyclical conditions (Benign). The LHS chart shows the aggregate historical loan loss rate of the mortgage portfolio estimated by the SNB. The RHS table reports the loss rate estimated for each relevant period against the loss rate projected by the model. For the benign period, the estimated loss rate is the average reported loss rate reported by the IRB banks in 2018. The data are obtained by simulating the model with the parameters shown in Table 2.

For the "benign conditions" validation, the model is simulated under a baseline scenario whereby the unemployment rate improves by 10 basis points to 2.6 percent, mortgage rates increase gradually from 1.5 percent to 2.8 percent over two years, and house prices remain stable over 2019–20. The resulting expected loss rate of 0.06 percent for the average bank mortgage portfolio closely replicates the average 0.10 percent "expected" loan loss rate on mortgage claims reported by Swiss banks in 2018 using their internal-based rating models (Figure 7). The expected loss rate is somewhat higher than the incurred credit loss measure for the Swiss mortgage portfolio of 0.04 percent in 2018, reflecting the backward-looking property of the latter [36].

I. Assessment of Macroprudential Policy Measures

In this section, we discuss how the model can be used to inform the adequacy of macroprudential policies. There are two macroprudential measures aimed at reducing risks in the real estate market in Switzerland: (1) a sectoral CCyB at 2 percent of risk-weighted positions secured by residential property situated in Switzerland; and (2) a mandatory amortization to two-thirds of the property collateral value at origination over a 15-year period, with a linear repayment schedule.

---

[36] Our measure of default provides a point-in-time estimate and therefore is expected to be lower during benign conditions (like in 2018) than the through-the-cycle loss rate estimated by banks using their internal models.

First, we assess whether the size of the sectoral CCyB is sufficient to protect the banking sector against the stress scenario. Under the macroprudential framework presented in Section II, we evaluate whether the value of the LHS of the equation is negative:

$$E_{t,\tau,\Omega}\left(X_T\right)-K_t > \beta_t$$

where the LHS of the inequality denotes the amount of net systemic risk under current macroprudential buffers K_t and β_t parameterizes the risk tolerance of the Swiss authorities.

Under our stress scenario, capital depletion reaches 135 basis points, which represents 4.2 times the size of the CCyB. Netting out the average provisions on mortgage loans, the amount of "unexpected losses" would exceed the CCyB by 3.8 times. At the same time, the capital conservation buffer (CCB) could also be drawn to absorb credit losses from the mortgage portfolio. Projected mortgage losses would exhaust the sectoral CCyB and deplete about 50 percent of banks' CCB. Interestingly, the capacity of the CCyB buffer to absorb unexpected mortgage losses depends crucially on the risk-weight density of mortgage loans[37], pointing at the benefits of considering the linkages between micro- and macroprudential buffers. This analysis complements the analysis by Basten and Koch (2015), who examine the effect of the CCyB on the composition of mortgage supply in Switzerland. They find that capital-constrained banks with low capital cushions raise their mortgage rates relatively more than their competitors, triggering the shifting of new mortgage loan production from less to more resilient banks.

In the second exercise, we use a counterfactual analysis to investigate the sensitivity of credit risk losses to changes in amortization requirements[38]. By contrast to the CCyB buffer, mandatory amortization policies apply only to newly generated mortgages. Assuming unchanged underwriting standards, a change in the maximum amortization period has two offsetting effects on the liquidity constraint in equation (1). It reduces the outstanding balance of more recent vintages, which become riskier as the housing and economic cycles mature. Conversely, it tightens the amortization schedule, increasing affordability risk. At the same time, increasing the pace of amortization decreases the probability of negative home equity by reducing the outstanding balance in equation (2). This lessens the prepayment constraint conditional on borrower's financial distress. The impact of changing amortization requirements on the margin call channel is not straightforward to predict. While it reduces the risk of a margin call being triggered (by increasing the PiT LTV ratio), it at the same time

---

[37] The risk-weight density varies by LTV tranche. For exposures booked under the standardized approach, it ranges between 35 and 100 percent—the latter for tranches larger than 80 percent of the collateral value, or if the mortgage loan does not meet SBA self-regulation requirements. Banks using an internal ratings-based approach can apply lower risk-weights to non-income producing mortgages.

[38] While our assessment of the CCyB is limited to the assessment of the existing CCyB in Switzerland, the counterfactual analysis could be used to consider alternative calibrations of CCyB too. Finally, while in this section we assess whether CCyB is sufficient specific to a particular scenario, Section V shows how the desirable size of CCyB could be determined using quantile regression techniques.

exacerbates affordability risk conditional on a margin call being activated (as the horizon to satisfy the cash payment shrinks).

The counterfactual analysis quantifies the effect of lowering the maximum amortization period in 2014 from 20 to 10 years[39]. We assume that this rule applies to loan vintages issued in or after 2014. Our simulation results suggest that the aggregate effect is negative, with the overall loss rate increasing from 1.77 percent to 2.45 percent by 2020. The impact is an additional capital depletion of about 52 basis points.

This result is driven by the increase in the probability of financial distress from a tightening in the amortization schedule. The effect is non-linear in the initial LTI ratio. For new mortgages with $LTI \leq 3$, the probability of financial distress increases from 7.6 to 9.6 percent, whereas for high-risk new issuances with $LTI > 7$, this probability increases from 46.8 to 66.5 percent. This negative effect is lower for older mortgages, as expected. For mortgages issued before 2013, financial distress increases from 7.2 to 7.3 percent for low LTI mortgages, and from 46.9 to 49.0 for high LTI ratios. This outcome suggests that an early activation of macroprudential measures is crucial to increase policy effectiveness. Section V explores the timing of policy adjustment, where macroprudential measures are activated k quarters before the tail risk scenario materializes.

V. CALIBRATION OF MACROPRUDENTIAL POLICY TOOLS IN AUSTRIA

Following concerns on vulnerabilities relating to residential real estate, a set of borrower-based tools was added to the macroprudential toolkit in Austria, including LTV, DSTI, and DTI limits, in September 2017. Yet, like in many other countries, relatively mild past house price downturns in Austria, short time series of house prices and NPLs, and scarce (until recently) use of macroprudential policies pose limits to a statistical approach for the purpose of informing calibration of the new macroprudential tools. In such circumstances, structural models are particularly useful. In what follows, we show how to use the baseline model from Section III to help inform the calibration of the borrower-based tools in Austria through a forward-looking exercise. Specifically, if the aforementioned borrower-based tools were to be activated, which combination of the measures should be considered, and at what levels[40]?

To address this question, we proceed in four steps. First, we discuss the characteristics of the housing market in Austria that should be reflected in the model specification and calibration. Second, we propose a way of constructing the adverse scenario appropriate for the purposes of calibrating macroprudential tools. Third, we show how macroprudential policies can be

---

[39] The cost of the policy in terms of banks' aggregate effect on credit supply is outside the scope of the analysis.
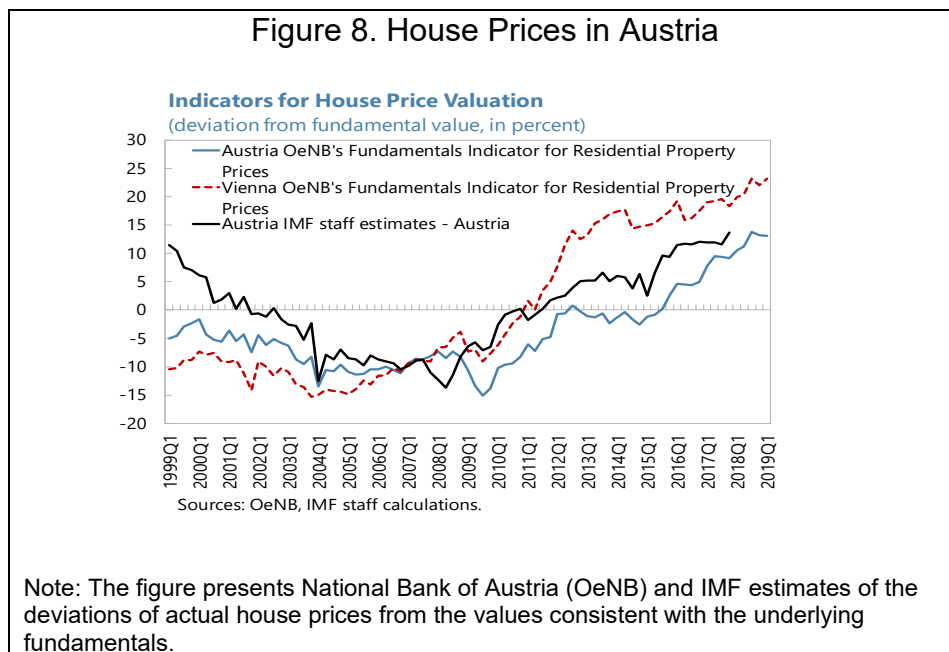
[40] Other papers that analyze borrower-based macroprudential tools in the Austrian context include Albacete and Linder (2017) and Albacete et al. (2018)

introduced to the model. Finally, we present a sample of results based on Austrian mortgage data.

A. Mortgage Market in Austria

Although Austrian households' indebtedness is below the euro area average, and relatively few households have a mortgage[41], there is evidence that the risk profile of new mortgage loans has been deteriorating in recent years. For example, loans with an LTV of 80 percent or above accounted for nearly 38 percent of new mortgages in 2018 (compared to 24 percent in 2012).

At the same time, favorable economic conditions and low interest rates have been supporting households' debt servicing capacity, with the average DSTI increasing but still hovering below 30 percent in recent years. Low interest rates have contributed to a rapid decline in the share of variable-rate household loans, which, however, remains high at 45 percent of new loans, thereby exposing households to the interest rate risk.

Figure 8. House Prices in Austria

Indicators for House Price Valuation
(deviation from fundamental value, in percent)

Sources: OeNB, IMF staff calculations.

Note: The figure presents National Bank of Austria (OeNB) and IMF estimates of the deviations of actual house prices from the values consistent with the underlying fundamentals.

House prices have grown rapidly in recent years and are estimated to be overvalued by about 10–-15 percent nationally and by over 20 percent in Vienna (Figure 8). The historically high growth rates in real estate transaction volumes (of 13 percent in 2018) have also been indicative of an overheating in the real estate market. Finally, real estate exposure has increased *across* the Austrian financial landscape in recent years. Housing loans in total assets of Austrian banks doubled from 8 percent in 2008 to 16 percent in 2018; the Austrian
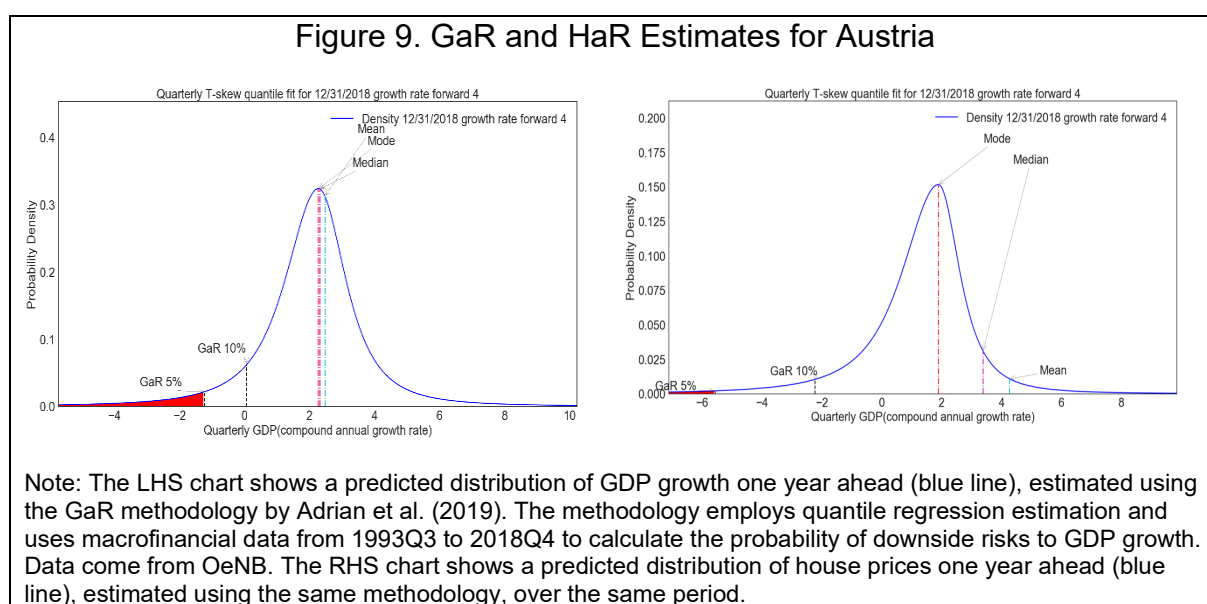
---

[41] Over 45 percent of the population rents rather than owns a house or an apartment.

insurance sector currently allocates about 8 percent of their total assets to real estate—the highest in the European Union; within the asset management industry, real estate investment funds have doubled in recent years; and a large part of new borrowing by nonfinancial corporates (NFCs) has been due to loans toward construction activities.

B. Defining the Adverse Scenario

Conceptually, calibration of macroprudential tools should be guided by the assessment of current downside risks to financial stability. Instead, bank stress tests usually assume extremely low-probability tail-risk scenarios. To address this issue, we use the GaR and HaR methodology, developed in Adrian et al. (2019) and in IMF (2017), which allows us to link the desirable tightness of macroprudential tools to the current level of key risks. Because GaR and HaR models are easy to update each quarter as new data become available, this makes the proposed approach suitable for a systematic application.

In the "at-Risk" approach, downside risks to real GDP growth and house price growth are proxied by the bottom 5th percentile of the forecasted distributions of future GDP and house prices. The methodology employs quantile regression estimation on macrofinancial data to calculate the predicted distribution of GDP or house prices one year ahead. In our application to Austria, the explanatory variables used for the HaR analysis include: house price growth, financial conditions index, private sector credit growth, house price misalignment, and GDP growth. Explanatory variables for the GaR include lagged GDP growth and financial conditions index. The sample covers the period 1993Q3–2018Q4. Figure 9 shows the predicted distributions of one-year-ahead quarterly GDP growth and house price growth, as of end-2018.

Figure 9. GaR and HaR Estimates for Austria

Note: The LHS chart shows a predicted distribution of GDP growth one year ahead (blue line), estimated using the GaR methodology by Adrian et al. (2019). The methodology employs quantile regression estimation and uses macrofinancial data from 1993Q3 to 2018Q4 to calculate the probability of downside risks to GDP growth. Data come from OeNB. The RHS chart shows a predicted distribution of house prices one year ahead (blue line), estimated using the same methodology, over the same period.

At that time, the median annualized quarterly growth rate over 2019 was projected to be about 2.1 percent (LHS chart), and there was a 5 percent likelihood that growth would fall to

-1.25 percent over the same horizon. For the house prices, the HaR model predicted a median real house price growth of around 3.2 percent and a growth of -5.5 percent at the lowest 5th percentile. For the purposes of our analysis, the 5th percentile estimates from GaR and HaR models are used to inform the size of income and house prices declines in the adverse scenario. Given the two-year horizon of the scenario, the realizations of GDP and house price growth rates from GaR and HaR are assumed to continue for two years[42]. The resulting peak-to-trough declines in real income and real house prices are shown in Table 3. Additionally, the increase in the unemployment rate is estimated based on the past relationship with GDP growth, and the increase in the interest rate on housing loans in the tail risk event is calibrated based on evidence from past recessions.

Given that the house price overvaluation has been estimated at 10–15 percent nationwide in 2018, the HaR-implied 11 percent decline in house prices over the adverse scenario seems relatively mild. Thus, as a robustness exercise, we also run the model under an alternative assumption of a 20 percent decline in real house prices during the two-year period (see Section V.E).

Table 3. Key Macroeconomic Assumptions in the Adverse Scenario for Austria	
Variable	Cumulative Percentage Change over Two Years (adverse)
Real disposable income	-2.5%
Real house price level	-11.0%
Unemployment rate	1.9%
Mortgage rate	1.4%

Note: The table shows the peak-to-trough changes in key macroeconomic variables that affect mortgage defaults and losses through equations (1)–(4). The change in unemployment is calibrated based on a linear regression of the change in unemployment and lagged GDP growth. The increase in the interest rate is calibrated based on the global financial crisis experience. During the crisis, the start-to-trough GDP fall was 3.65 percent, while the real rates on housing loans increased by 200 basis points between 2008Q2 and 2009Q2. This implies an increase in real interest rate for our 2.5 percent decline of GDP by 140 basis points.

C. Introducing Macroprudential Tools

The introduction of macroprudential borrower-based limits to the model from Section III is straightforward. For that, we simply assume macroprudential policies are introduced k quarters before the adverse scenario materializes. During this time, the macroprudential limits affect the LTVs and DSTIs of new flows of mortgages:

- First, we assume that in the absence of macroprudential measures, mortgage flows in the next k quarters will be similar (in terms of volume, LTV, DTI, and DSTI distributions) to the average flows observed in the last four quarters of available data.

---

[42] For simplicity, the exercise considered GaR and HaR analyses separately, but the 5th percentile GDP growth value obtained from the GaR model could be used to inform the HaR predictions.

Meanwhile, some of the outstanding loans mature—with the volume of maturing loans similar to the one observed in recent quarters.

- Macroprudential limits reduce the relative mass of loans with LTVs or DSTIs above the limits set by the regulators: to zero if "hard" limits are introduced, and to a certain percentage (of total new loans) if so-called "speed limits" are allowed instead[43].

- We assume that there is a "bunching" of new loans just below the regulatory limits. That is, among the loans complying with regulatory limits, the relative share of loans with LTV/DSTI ratios *just* below the limits increases. This is because some of the borrowers that would otherwise obtain loans with LTVs or DSTIs above the limits now agree to loans with the highest allowed LTV/DSTI ratios. We assume that the bunching" effect is proportional to the decline in the mass of loans above the limits[44].

During the *k* quarters, household income and house prices are assumed to grow at the median values (adjusted to quarterly frequency) predicted from the GaR and HaR exercises. In the case of Austria, we also assume no changes in the unemployment rate and in the mortgage interest rate before the adverse scenario materializes[45].

The model is flexible in allowing several alternative calibrations of borrower-based macroprudential limits. In the application for Austria, we consider a (1) range of LTV limits; (2) range of DSTI limits; and (3) a combination of LTV-DSTI limits. DSTI limits affect the DSTI in the stressed sale formula but can affect the LTV distribution as well (since the information on joint LTV-DSTI distribution is available). In general, DTI limits could be also introduced in the model, but in the case of Austria, the way that the DTI statistics are calculated and reported in the regulatory data makes it difficult to incorporate the DTI ratios in the model in a straightforward manner.

We also distinguish between hard limits and speed limits, where in the latter case a pre-defined share of loans is allowed not to comply with the regulatory limit. Finally, given the purpose of the exercise, we use data on the aggregate, banking sector-wide portfolio of mortgages instead of bank-level information. For each choice of the macroprudential tools, we compare the losses on the aggregate mortgage portfolio generated in the adverse scenario, with the losses observed in the absence of any limits.

---

[43] An LTV limit of 80 percent with a speed limit of 10 percent means that a maximum of 10 percent of new loans can have an LTV of more than 80 percent.

[44] That is, if there are 10 percent of loans with an LTV above 80 percent, we assume that after the introduction of an LTV limit of 80 percent, the relative share of loans with an LTV ratio of just less than 80 percent in total new loans increases by 10 percent.

[45] Depending on the macroeconomic outlook, different assumptions for unemployment and interest rates can be made.

D. Calibration and Data Transformations

The Austrian dataset used in the calibration covers about two-thirds of all new housing loans *issuances* at quarterly frequency and goes back to 2011. The latest datapoint was 2018Q4. The data capture a rich set of properties of loans at origination, including distributions by (1) LTV; (2) DSTI; (3) DTI; (4) LTV-DSTI jointly; (5) LTV-DTI jointly; (6) a share of variable-rate loans in new loans; and (7) the average maturity of new loans.

As the data provide information on past vintages of loans, we do not need to back out vintage-LTV buckets ourselves (contrary to the Switzerland case). However, to study the impact of shocks and the role of policies, we would like to have information on the *current* LTV and DSTI distribution (PiT LTVs and DSTIs). As the data capture properties of loans at origination, we make additional calculations to obtain estimates of PiT LTVs and DSTIs of outstanding loans (by LTV-vintage bucket) as of 2018Q4 (see Appendix III for details)[46].

Given that the data report only the relative share of new loans by different risk characteristics in total new loans issued in a given quarter (vintage) and do not report volumes of new loan issuances, we need to calculate the absolute shares of mortgages in each LTV-vintage bucket in the banking system's loan portfolio as of 2018Q4. For this purpose, we use time series of new mortgage flows and mortgage stocks available at the National Bank of Austria (OeNB) website. We capture mortgage loans originated before 2011 by assuming they have similar risk characteristics as the loans in the earliest eight vintages in our database on average (2011Q1–2012Q4)[47].

As Austria has not experienced a severe house price downturn or a credit distress event in the past, we calibrate the parameters driving the probability of financial distress in equation (1) following Harrison and Mathew (2008), that is, based on the UK experience in the early 1990s. We set the parameter D to match the expected probabilities of default reported by banks over the past three years. Other parameters are set to capture Austria-specific characteristics of the housing market. Table 4 provides values of all calibrated parameters.

Following Harrison and Mathew (2008), $\Phi\left(DSTI_{i,t-1}\right)$ in equation (1) is allowed to vary with the level of DSTI non-linearly (see Section III for motivation). In our case, the DSTI includes both amortization and interest payments, so we set the lower DSTI threshold, above which $\Phi\left(DSTI_{i,t-1}\right)$ starts to increase somewhat higher than the 10 percent in Harrison and Mathew (2008), who consider interest payments only. We set the upper DSTI threshold, above which $\Phi\left(DSTI_{i,t-1}\right)=1$ at 30 percent. Parameter β_3 is larger than zero only when $\Delta U_t > 0$, that is,

---

[46] Similar calculations had to be done in the case of Switzerland.

[47] In other words, we assume that loans originated before 2010 have similar LTV-DSTI characteristics to the loans originated in 2010–11.

only increases in the unemployment rate are assumed to have a nonlinear and positive impact on the DSTI.

We use historical data on the share of fixed- versus floating-rate mortgages at origination when calculating the NPV of an outstanding loan in equation (3). In particular, in the portfolio simulation, we apply the interest rate change only to a fraction of loans in each bucket—equal to the historical share of floating-rate loans in that vintage.
We calibrate the transaction cost C to match the sum of average real estate transfer tax rates and registration fees reported for Austria in Schneider and Wagner (2015).

We use the average loan maturity at origination (T^s) reported by the OeNB, and we set the discount rate, at which foreclosed house is sold by the bank (δ) at 20 percent, based on discussions with OeNB experts. We set the risk-free rate, applied for discounting at close to zero, and apply a 200-basis point risk premium for discounting revenues from foreclosed assets[48]. The time needed for a sale of a foreclosed property is set at 1.25 years, but we test sensitivity to different values of this parameter.

Finally, we draw the house prices in equation (2) from a normal distribution with a mean calculated by adjusting the real house price level in 2018Q4 by the assumed house price decline in the adverse scenario (Table 3). The parameter σ_P denotes the standard deviation of the house price distribution, and for Austria we set it at 15 percent (based on discussions with local housing market experts).

Table 4. Model Calibration for Austria				
Equation (1)			Equations (2)-(4)	
Parameter	Value		Parameter	Value
$\phi(DSTI)$	$=\begin{cases} 0 \; if \; DSTI < 15\% \\ \dfrac{DSTI - 15\%}{30\% - 15\%} \; if \; DSTI \in [15\%, 30\%] \\ 1 \; if \; DSTI > 30\% \end{cases}$		C	5% of house value
D	0.2		Ts	25
β_1	0.0003		rf	0.1%
γ	2.5		spread	2%
β_2	0.006		δ	20%
β_3	0.007 if $\Delta U_t > 0$ and 0 otherwise		Q	1.25
α	1		σ_P	15%

Note: This table reports the core parameter values used to project credit risk losses for the Austrian banking sector.

---

[48] See Harrison and Mathew (2008) for a discussion.

E. Results

In what follows, we focus on the case when *k=8*, that is, we allow new mortgages to be originated for eight quarters before the adverse scenario materializes. In general, the effectiveness of macroprudential limits will depend on how long before the realization of the adverse scenario they were introduced. When we change the number of quarters to *k=4*, the PDs and portfolio losses increase somewhat, but the ordering of different macroprudential tools calibrations (Table 6) remains the same.

Table 5 shows, in the absence of any macroprudential limits, PDs, LGDs, and annualized losses (in percent of the relevant mortgage portfolio) in the adverse scenario for the system-wide mortgage portfolio, and for the mortgage flows that are assumed to materialize in the next eight quarters, but before the adverse scenario begins ("new mortgages").

In the absence of macroprudential limits, the annualized losses stand at 0.8 percent of the aggregate portfolio size, and the average PD is equal to 1.9 percent (annualized). The newly issued mortgages seem to be the main driver of the total mortgage losses[49], with the annualized PD of 3.9 percent, and annualized losses at 1.6 percent for the subgroup of loans originated in eight quarters ahead of the adverse scenario.

Table 5. Losses on Mortgage Portfolios in the Absence of Macroprudential Limits (Percent)			
	1-Year PD	LGD	Expected Annualized Losses
Adverse Scenario			
System wide mortgage portfolio	1.9	26.6	0.8
of which: new mortgages	3.9	34.0	1.6
Sensitivity Analysis			
Model with borrower financial wealth			
System wide mortgage portfolio	1.6	28.5	0.7
of which: new mortgages	3.4	33.7	1.5
A higher interest rate increase			
System wide mortgage portfolio	3.4	32.0	1.5
of which: new mortgages	6.9	40.0	3.1
A larger house price decline			
System wide mortgage portfolio	2.3	29.2	0.9
of which: new mortgages	4.5	37.7	2.0

Note: The top section shows LGDs, annualized PDs, and annualized expected losses over the two-year adverse scenario described in Table 3 for the banking system-wide mortgage portfolio (upper row), and for the mortgage issuances simulated in eight quarters before the adverse scenario materializes (bottom row). The "Sensitivity Analysis" section shows LGDs, PDs, and cumulative losses in three alternative cases: (1) in an adverse scenario, but when accounting for household financial wealth in the default equations (1)-(4); (2) in an adverse scenario with a real interest rate increase of 200 basis points; and (3) in an adverse scenario with a real house price decline of 20 percent.

[49] The finding that recent mortgage issuances drive credit losses is a regularity confirmed in many bank stress tests.

Table 5 ("Sensitivity Analysis" section) also shows how the expected losses change under three alternative specifications. First, a potential drawback of our definition of default is that it does not allow borrowers that are in financial distress to draw on their savings to continue mortgage repayments. In the first sensitivity exercise, we thus augment the default conditions (1)–(4) to incorporate borrowers' financial assets. We do so by adding to the LHS of equation (2) the median estimate of financial assets of Austrian households that own a mortgage from the ECB's Household Finance and Consumption Survey. As Table 5 shows, the annualized losses in the adverse scenario decline in this case by about 8 percent for the total mortgage portfolio (from 0.8 to 0.7 percent), and by 6 percent for new mortgages (from 1.6 to 1.5 percent). The relatively smaller decline in the case of new mortgages is intuitive, as the mortgage payments and the NPV are likely higher for new loans, and thus financial assets are more frequently insufficient for preventing the borrowers from defaulting. In the other two sensitivity exercises, we augment the adverse scenario to consider (1) a larger increase in real interest rate (of 200 basis points); and (2) a larger real house price decline (of 20 percent). As expected, the projected annualized losses increase in the two alternative scenarios, and relatively more so for the new mortgages. The increase in expected losses is particularly pronounced when considering larger interest rate increases—consistent with a relatively high share of variable-rate loans in Austria.

When we benchmark our results against credit losses in advanced countries during systemic banking crises, we find that the annualized loss rate for newly issued mortgages would imply a three-year cumulative NPL ratio of 12.9 percent under the scenario where real house prices decline of 20 percent. Given the evidence of overvaluation in the Austrian housing market in recent years, we view it as a plausible downside scenario. The NPL ratio of 12.9 percent matches the median peak NPL across past banking crises in advanced economies, reported in Laeven and Valencia (2018), under the assumption of no write-offs or recoveries.

Table 6. Losses on new mortgages in the presence of macroprudential limits (Percent)										
		hard limits					speed limit of 20 percent			
LTV	none	80	none	80	80	90	80	none	80	80	90
DSTI	none	none	40	30	40	40	none	40	30	40	40
PD	3.9	2.7	3.2	1.3	2.2	2.7	3.3	4.0	2.3	3.3	3.7
LGD	34.0	31.9	31.8	31.8	31.8	32.1	32.9	34.1	32.9	32.9	33.4
Exp. Annual Loss	1.6	1.0	1.3	0.5	0.8	1.0	1.3	1.6	0.9	1.3	1.5

Note: Table shows LGDs, annualized PDs and annualized expected losses over the 2-year adverse scenario described in Table 3 for the banking system-wide mortgage issuances simulated in 8 quarters before the adverse scenario materializes, when different combinations of borrower-based macroprudential limits are applied.

Next, we run the model under different macroprudential policy limits calibrations. As macroprudential tools will only affect the new flows of mortgages, Table 6 reports key credit risk indicators for the new mortgages under a range of different macroprudential limits. For simplicity, we present results for ten alternative calibrations of macroprudential limits and focus on LTV and DSTI limits. However, DTI limits, and maturity limits can be introduced in the model as well.

A few observations follow from Table 6. First, different combinations of macroprudential limits can have a similar impact on the expected losses in an adverse scenario. For example, a combination of hard LTV-DSTI limits of 80-40 percent results in an annualized loss (0.8 percent) on new mortgages similar to the loss (0.9 percent annualized) obtained through a combination of the same limits of 80-30 percent, but with a speed limit of 20 percent. This implies that policymakers can choose between different calibrations of macroprudential tools to obtain the same reduction in the expected loss rates. When selecting the preferred set of limits, other factors can be considered—for example, the ease of implementation of different limits and their impact on banks' business models.

Second, a standalone DSTI limit of 40 percent is not effective in reducing the frequency of loan defaults. For example, among regulations with a speed limit, the expected loss is the same for a combination of LTV-DSTI limits of 80-40 percent and for a standalone LTV limit of 80 percent. For a hard DSTI limit of 40 percent, the PD and annualized losses declines are relatively modest (from 3.9 to 3.2 percent and from 1.6 to 1.3 percent, respectively). A likely explanation is that historically low lending rates in recent years have been driving the DSTIs of new loans down. In fact, the system-wide average DSTI for new mortgage flows was somewhat below 25 percent in 2018. Thus, it is likely that a DSTI limit of 40 or even 30 percent would affect only a small portion of new mortgages.

Finally, appropriately calibrated macroprudential limits with speed limits can achieve the same objectives (in terms of bank losses) as hard limits. A potential benefit of using speed limits rather than hard limits is that they allow banks some flexibility in granting loans to customers and thus affect their business models to a lesser extent.

F.   Which Macroprudential Limits to Choose?

A natural next question is: which of the different combinations of macroprudential limits should be the preferred one? As indicated in Section II, this choice will partially depend on factors outside the model of credit default, including, for example, regulatory tolerance for risk. Ideally, the solution should also take into account any general equilibrium effects. These should capture the impact of the new limits on bank credit and house prices (and through credit and house prices—also on GDP growth) and the feedback effects from the lower credit and house valuations on PDs and LGDs.

While these considerations remain beyond the scope of this paper, the growing empirical evidence can be used to inform the analysis presented here. For example, using household-level data from different European countries, Laliotis et al. (2019) find that LTV limits have a non-marginal impact on house prices and credit only once they fall below 80 percent. Instead, Alam et al. (2019) show that the impact of the LTV limits on credit growth is non-linear in the size of the tightening relative to the initial average LTV. Finally, Gross and Población (2017) quantify the second-round effect of macroprudential limits in an integrated micro-/macroeconomic framework. Gross et al. (2020) consider a nonlinear macrofinancial simulation framework required to account for two-way macrofinancial dependencies between the banking sector and the real economy.

Instead, in what follows, we propose a "rule of thumb" that can be used to guide the selection of preferred macroprudential limits once the second-round general-equilibrium effects are accounted for. The simple principle compares the expected losses on new mortgages (those subject to macroprudential limits) with those on less risky older mortgage vintages, granted before the borrower limits are introduced. Arguably, if a given calibration of macroprudential limits leads to a loss rate on new mortgages considerably lower than the losses on older vintages, it might be considered too tight relative to the reference portfolio. In our example, the annualized loss rate on the total mortgage portfolio (a proxy of losses on "old" mortgages) is 0.8 percent. Among the macroprudential limits considered, a combination of LTV- DSTI limits of 80-30 percent with a speed limit of 20 percent, and hard limits on LTV-DSTI of 80-40 percent achieve a similar rate for new loan issuances.

Moving beyond this simple rule of thumb and formalizing the ideas presented in this paper, the systemic risk framework presented in Section II suggests that authorities may need to tighten macroprudential instruments to ensure that the riskiness of new loan production X_T^{NEW} is not higher than that of the reference portfolio, X_T^{ref} in:

$$\min_{B,p,\lambda} \left| E_{t,B,\Omega}\left(X_T^{new}\right) - E_{t,\Omega}\left(X_T^{ref}\right) \right|$$
$$s.t. \Pr\left(B\left(L_t^{new}\right) > p\right) \le \lambda$$

If $E_{t,\Omega}\left(X_T^{ref}\right)$ is calibrated to the peak NPL observed in Austria during the global financial crisis (4.1 percent, see Valencia and Laeven 2018), then the corresponding reference default rate will be 2.1 percent. Thus, the objective function above would reach the value of zero if macroprudential instruments on new loans are adjusted to either a combined LTV- DSTI limit of 80-30 percent with a speed limit of 20 percent, or to a hard limit on LTV-DSTI of 80-40 percent.

VI. CONCLUSIONS

In this paper we propose a semi-structural approach for credit risk analysis, when the scarcity of data, absence of tail events, or presence of structural shifts renders statistical models unreliable. This is particularly the case for countries that have not experienced large house price or economic downturns in the past, or for which adjustments to the regulatory framework have altered the loan default process. Importantly, compared to other structural methods, our approach does not require access to micro-level data, but relies on more readily available regulatory information on loan contracts at the risk bucket and bank portfolio level, which can be updated as often as the quarterly frequency. At the same time, given the sensitivity of default rates to vintage flows and state variables, the approach suggests the beneficial impact of collecting regulatory granular data on vintage disclosures and risk buckets not just for supervisory purposes but also to safeguard financial stability.

The basis of our framework is a semi-structural model of default risk, first defined in Harrison and Mathew (2008), which introduces a "double trigger" condition for borrower default based on the ability-to-pay principle, and uses simulation techniques to project bank credit losses under adverse macrofinancial conditions. We extend this model along several dimensions to capture mortgage characteristics, housing finance modalities, and changes in policy frameworks and macroprudential measures. We recalibrate the model to enhance performance in country-specific applications, backtest the model outputs to test performance against relevant historical episodes (including crisis and recovery periods), and assess the impact of a mortgage prepayment penalty on the default process. We also conduct a wide range of sensitivity tests and robustness checks to test the impact of underlying modeling assumptions on model outcomes.

This paper aims at supporting the efforts of macroprudential authorities by presenting a conceptual framework of systemic risk. When stress test results point at the deterioration in the credit risk profile of new mortgages, we propose a rule to guide changes in macroprudential policy as to minimize the authorities' loss function relative to a benchmark portfolio. The projection of losses in the mortgage market allows making judgments on the adequacy of bank capital buffers to absorb unexpected losses. We also show how macroprudential borrower-based limits can be introduced in the model in a forward-looking manner. The model simulations help assess the effectiveness of different macroprudential instruments and their calibrations to reduce systemic risk, and reveal insights into the timely execution of macroprudential policy.

Throughout the paper, we demostrate the flexibility of the modeling approach. For each application, we show how the model can be calibrated depending on data availability, country-specific characteristics, and structural changes. While the model was calibrated based on pre-COVOD information, it can still provide useful insights during the pandemic due to its structural approach, the use of simulations, its vintage granularity, and the control for policy changes. The calibration of the model to COVID-19 shocks and the effectiveness of pandemic-related policy measures to mitigage systemic risk is left for future research.

REFERENCES

Adrian, T., N. Boyarchenko, and D. Giannone, 2016. "Vulnerable Growth." *American Economic Review,* 109(4), 1263-89.

Albacete, N., and P. Linder, 2017. "Simulating the impact of borrower-based macroprudential policies on mortgages and the real estate sector in Austria—evidence from the Household Finance and Consumption Survey 2014," OeNB *Financial Stability Report* Vol. 33, 52-68.

————, P. Fessler, and P. Linder, 2018. "One policy to rule them all? On the effectiveness of LTV, DTI and DSTI ratio limits as macroprudential policy tools," OeNB *Financial Stability Report* Vol. 35, 52-68.

Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M. Nier, E. and N. Wang, 2019. "Digging Deeper—Evidence on the Effects of Macroprudential Policies from a New Database," IMF Working Paper 19/66.

Bank for International Settlements, 2018. "Stress Testing Principles," Basel Committee on Banking Supervision, October.

————, 2012. "Operationalizing the selection and application of macroprudential instruments," Committee on the Global Financial System, CGFS Paper No. 48, December.

Basten, C., and C. Koch, 2015. "Higher Bank Capital Requirements and Mortgage Pricing: Evidence from the Countercyclical Capital Buffer (CCB)," BIS Working Paper No. 511, September.

Bhutta, N., J. Dokko, and H. Shan, 2010. "The depth of negative equity and mortgage default decisions," Finance and Economics Discussion Series 2010-35, Federal Reserve Board.

Breuer, T., and M. Summer, 2018. "Systematic Systemic Stress Tests," OeNB Working Paper 225, December.

Elul, R., Souleles, N., Chomsisengphet, S., Glennon, D., and R. Hung, 2010. "What 'Triggers' Mortgage Default?" *The American Economic Review,* Vol. 100, No. 2, Papers and Proceedings, 490-94, May.

European Central Bank, 2007. "The impact of short-term interest rates on bank credit risk taking," *Financial Stability Review,* December.

Financial Conduct Authority, 2015. "Methods for analyzing mortgage markets," Occasional Paper No. 11.

FINMA, 2019a. "Mortgages for investment properties: FINMA recognizes adjustments to self-regulation," August.

———, 2019b, "Action is now needed on investment property," speech by Mark Branson at the annual media conference, April.

Foote, C., K. Gerardi, and P. Willen, 2009. "Negative equity and foreclosure: No easy answers," in *NBER Macroeconomic Annual 2009.* Chicago: University of Chicago Press.

Gross, M., L. Mindaugas, and L. Valderrama, 2020. "The Macro-Financial System Simulator (MASS)," IMF Working Paper (forthcoming).

———, and J. Población, 2017. "Assessing the efficacy of borrower-based macroprudential policy using an integrated micro-macro model for European households," *Economic Modelling* Vol. 61, 510-28.

Harrison, I., and C. Mathew, 2008. "Project TUI: A Structural Approach to the Understanding and Measurement of Residential Mortgage Lending Risk," Reserve Bank of New Zealand.

International Monetary Fund, 2020a. "Austria Financial Sector Assessment Program: Technical Note—Macroprudential Policy Framework and Tools," IMF Country Report 20/64, March.

———, 2020b. "Canada Financial Sector Assessment Program: Technical Note—Stress Testing and Financial Stability Analysis," IMF Country Report 20/16, January.

———, 2019a. "Switzerland Financial Sector Assessment Program: Technical Note—Stress Testing the Banking Sector," IMF Country Report 19/189, June.

———, 2019b. "Lower for Longer," *Global Financial Stability Report,* Chapter 1, October. Washington: International Monetary Fund.

———, 2017. "Is Growth at Risk?" *Global Financial Stability Report,* Chapter 1, October. Washington: International Monetary Fund.

———, 2014. "Staff Guidance Note on Macroprudential Policy," IMF Policy Paper, December.

Jurca, P., Klacso J., Tereanu, E., Forletta, M. and M. Gross, M., , 2019. "The effectiveness of borrower-based macroprudential measures: a quantitative analysis for Slovakia," IMF Working Paper (forthcoming).

Laeven, L., and F. Valencia, 2018. "Systemic Banking Crises Revisited," IMF Working Paper 18/206.

Laliotis, D., Buesa, A., Leber, M., and J. Poblacion, 2019. "An Agent-Based Model for the Assessment of LTV Caps," ECB Working Paper 2294, July.

Lazarov, V., and M. Hinterschweiger, 2018. "Determinants of distress in the UK owner-occupier and buy-to-let mortgage markets," Bank of England Staff Working Paper No. 760, October.

Nier, E., Popa, R., Shamloo, M., and L. Voinea, 2019. "Debt Service and Default: Calibrating Macroprudential Policy Using Micro Data," IMF Working Paper 19/82.

Pennington-Cross, A., 2003. "Subprime and Prime Mortgages: Loss Distributions," OFHEO Working Papers 03-1.

Schneider, M., and K. Wagner, 2015. "Housing Markets in Austria, Germany and Switzerland," *Monetary Policy and the Economy,* Oesterreichische Nationalbank, Issue 1, 42-58.

Appendix I. Calculation of Penalty for Early Prepayment

The cost of terminating ahead of schedule is given by the net present value of the loan:

$$NPV_{i,t} = L_{i,t} + \sum_{j=0}^{T-1} \frac{r_{i,t} L_{i,t}(1-\frac{j}{T_{i,t}})}{(1+r^f)^j}, \qquad (A.1)$$

where $L_{i,t}$ is the outstanding principal and $r_{i,t}$ is the interest rate of the mortgage at time t. For floating-rate mortgages, it denotes the libor rate at time t; for rollover mortgages, it is the interest rate prevailing at the last resetting period. The equation assumes a linear repayment schedule during the remaining maturity of the loan, $T_{i,t}$. Because the lender recovers the full amount of money owed at time t, it can reinvest that money immediately and earn the risk-free return r^f. This return is then deducted from the amount owed by the borrower.

The first term in (A.1) is the outstanding value of the loan at time t. Under a linear amortization schedule $L_{i,t}$ is defined by:

$$L_{i,t} = \frac{T_{i,t}}{M_i} \cdot L_{i,s}$$

where M_i denotes the maturity at origination and $L_{i,s}$ represents the face value of the loan at origination. The second term in (A.1) captures the net present value of foregone interest. It can be decomposed into a geometric sum (A) and an arithmetic–geometric sequence (B). The sum of the terms of the geometric sequence is equal to the following expression:

$$A = \left(r_{i,t} \cdot L_{i,t}\right) \cdot \left(\frac{1+r_{i,t}^f}{r_{i,t}^f}\right) \cdot \left(1-\frac{1}{1+r_{i,t}^f}\right)^T$$

The sum of the terms of the arithmetic–geometric sequence in B is denoted by:

$$B = \left(r_{i,t} \cdot L_{i,t}\right) \cdot \left(\frac{1}{1+r_{i,t}^f}\right)^T \cdot \left[\frac{1+r_{i,t}^f}{r_{i,t}^f} - \frac{\left(1+r_{i,t}^f\right)^T - 1}{T \cdot \frac{\left(r_{i,t}^f\right)^2}{\left(1+r_{i,t}^f\right)}}\right].$$

After some algebraic manipulation, the net present value of the loan can be denoted by:

$$NPV_t = L_{i,t} + \left(r_{i,t} \cdot L_{i,t}\right) \cdot \left(\frac{1}{r_{i,t}^f \cdot \left(1+r_{i,t}^f\right)^{T-1}}\right)^T \cdot \left[\left(r_{i,t}^f\right)^T + 1 - \frac{\left(1+r_{i,t}^f\right)^T - 1}{T \cdot r_{i,t}^f}\right].$$

Appendix II. Calculation of LTV Distribution under Alternative Approach in Section IV

This appendix explains the procedure used to generate PiT LTV shares for each outstanding vintage in the mortgage portfolio, under the assumption that LTV distributions are equal at origination.

We denote the set of LTV buckets by $B = \{b_1, b_2, b_3, b_4, b_5\}$, where buckets are labeled in increasing order of LTV. We have information on the PiT LTV shares of the *stock* of mortgages at time t represented by $\{\beta_b\}_{b=1}^{5}$. We assume a candidate distribution of mortgage shares at issuance LTV_s^{orig} denoted by $\{\hat{\alpha}_b\}_{b=1}^{5}$.

For each LTV bucket, we compute the "second mortgage" and apply the amortization rule (A in the formula below). The amortization schedule is a function of LTV_s^{orig} which defines the portion of the mortgage subject to amortization, and the year of issuance s, which determines the maximum amortization period. We revalue the collateral at time t at current market prices to calculate the PiT LTV ratio, where g denotes the growth rate of real estate prices:

$$LTV_{s,t,b}^{PiT} = \frac{\left(1 - \sum_{i=1}^{t-s} A\left(LTV_{s,b}^{orig}, s, i\right)\right) \cdot L_{s,b}}{HP_s \cdot \prod_{k=1}^{t-s} \left(1 + g_{s+k}\right)}$$

The share of outstanding mortgages with PiT LTV=b at time t is computed as:

$$\hat{\beta}_{b,t} = \sum_{s=t_0}^{t} \gamma_s \cdot \sum_{k=1}^{5} \hat{\alpha}_k \cdot I_{s,t,b,k}$$

where γ_s is the share of vintage s in the outstanding stock at time t, and $I_{s,t,b,k} \equiv I\left[LTV_{s,t,b}^{PiT} \in b_k\right]$ is a time-varying indicator function taking a value of 1 if the PiT LTV value of a loan falls into bucket b_k, and 0 otherwise.

The value of $\{\alpha_b\}_{b=1}^{5}$ is the solution to the multiple equation system:

$$\beta_{b,t} = \sum_{s=t_0}^{t} \gamma_s \cdot \sum_{k=1}^{5} \alpha_k \cdot I_{s,t,b,k}$$

where $\{\beta_b\}_{b=1}^{5}$ is the LTV distribution observed at time t. Once we pin down the value of $\{\alpha_b\}_{b=1}^{5}$ we can compute the PiT shares for each vintage-LTV bucket applying the amortization rule discussed above.

Appendix III. Calculation of Point-in-Time Loan Value, LTVs, and DSTIs in Section V

These values are computed as of 2018Q4:

$$L_{h,2018Q4} = \frac{\left(LTV_{h,origin} \times P_{origin} \times \frac{T_{h,2018Q4}}{\overline{T}_h}\right)}{P_t}, \qquad (A.2)$$

$$Income_{h,origin} = \frac{L_{h,origin}}{DTI_{h,origin}} \qquad (A.3)$$

$$Income_{h,2018Q4} = Income_{h,origin} \times (1 + g^{cum}_{origin:2018Q4}) \qquad (A.4)$$

$$LTV_{h,2018Q4} = \frac{L_{h,2018Q4}}{P_t}, \qquad (A.5)$$

$$DSTI_{h,2018Q4} = \frac{\left(LTV_{h,origin} \times P_{origin} \times \left(\frac{1}{\overline{T}_h} + r \times \frac{T_{h,2018Q4}}{\overline{T}_h}\right)\right)}{Income_{h,2018Q4}}, \qquad (A.6)$$

where $\overline{T}_h$ stands for the average maturity at origination of loans in the vintage-LTV bucket h. The outstanding value of a loan in equation (A.2) is derived assuming that the current LTV is equal to the LTV at origination net of repayments made. To compute (A.2) we use information on average nationwide house prices available at quarterly frequency. Equations (A.3)–(A.4) compute the borrower's income at the time of mortgage origination (using information on the DTI at origination) and the income as of 2018Q4. For the latter, we multiply the past income by the cumulative growth rate of real household income, $g^{cum}_{origin:2018Q4}$ (using data on real household income growth from the Organization for Economic Co-operation and Development—OECD). Finally, we compute LTVs and DSTIs on the outstanding loans in bucket h using equations (A.5)–(A.6).