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A DSGE model for macroprudential policy in Morocco

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A DSGE model for macroprudential policy in Morocco[1]

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ABSTRACT

This working paper presents a DSGE model for macroprudential analysis in Morocco. The model has been calibrated to match stylized facts of the Moroccan financial sector and can be used for macroprudential policy analysis, scenario building, or stress-testing. The model provides a top-down perspective on the financial sector stability, complementing the more traditional financial supervision tools currently in use at Bank Al-Maghrib. The paper describes the model structure and highlights its features that make it suitable for the analysis of macroprudential issues– strong role of nonlinearities, endogenous macro-financial feedback loops, and explicit description of the aggregate bank balance sheet. The paper presents three simulations to illustrate key transmission mechanisms: (i) Macroeconomic impact of an increase in equity capital; (ii) The role of capital flows sensitivity to capital buffers building requirement and (iii) The Impact of the COVID-19 crisis on the banking sector.

JEL Classification Numbers: C58, D53, E32, E44, E58, F47.

Keywords: Macroprudential policy, Macroeconomic modeling, Morocco, Financial sector.

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1. Introduction

DSGE models have become prominent in central banks for monetary and macroprudential policy purposes. Since the 2008 financial crisis, these models have undergone important developments in modeling the interaction of the real and financial spheres[3]. However, there has been comparatively little success in operationalizing the DSGE models for purposes of analyzing practical, policy-relevant questions related to macroprudential stability. This paper presents results from an effort to bring insights from theoretical DSGE models into practical use at Bank Al-Maghrib.

In emerging and developing countries, where the banking sector represents the bulk of the financial system, it is important to understand how interactions between the real economy and the financial sector are affected by the state of banks' balance sheets. For example, banks may choose to pass on shocks to performance of particular asset classes (loans, real estate assets, market activities) or liabilities (dividends, equity), on the real economy with differentiated effects. The permanent or transitory nature of these shocks, as well as the speed with which banks adjust to them, also have different implications. Finally, the structural nature of the DSGE models allows the study of a degree of coordination between monetary and macroprudential policies and can help modulate the magnitude of these interactions. DSGE models allow us, thus, to examine all these questions.

The particularity of DSGE models for financial stability is the role that these models give to non-linearities in the interactions of the real economy and financial system in times of crisis. While in normal times these interactions are of no significant consequence aside from overall increase in economy-wide productivity due to efficient allocation of capital, the behavior might change abruptly in crisis periods. Linearized models cannot capture this feature which is crucial for modeling macroprudential issues. The model presented in this paper is nonlinear and therefore particularly well suited to the analysis of crisis scenarios, or more generally of downside risks. The model use can nevertheless be also used to the study of the economy's reactions to shocks in normal times. In order to promote the operational flexibility of the model, we have chosen a semi-structural model where we closely follow rigorous micro-foundations of DSGE models where possible but deviate to add equations to the model and to modify the calibration of the parameters in order to fit the stylized facts and carry out particular simulations as necessary.

The model is constructed by taking the aggregate view of the financial sector and the real economy – the so-called “top-down” approach. The model describes an aggregate balance sheet of the banking sector whose assets and liabilities interact with the real sector. This model can therefore be used as a complement to stress test exercises which are generally based on a "bottom up" approach in which shocks impact the banks' balance sheets on an individual basis before obtaining an aggregate effect.

This paper describes the main features of the model and illustrates its key transmission mechanisms through theoretical and data-based simulations. The rest of the document is presented as follows. The first section presents an overview of the recent debate related to macro-financial modeling and situates our model to the literature. The second introduces the general structure of the model while the third sections presents a more detailed description. The last section shares the simulation results of three different simulations.

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[3] *As examples of Central Banks publications: Angelini et al. (2012, European Central Bank), Bennani et al. (2017, Banque de France), Henry and Martin (2017, European Central Bank) and Hinterschweiger et al. (2021, Bank of England).*

2. Literature Review

The literature on macro-financial modeling expanded rapidly in the last decade as many policymaking institutions were assigned new powers and responsibilities related to maintaining macroprudential stability. Both academia and institutions such as the Bank of International Settlements (BIS) and the IMF provided valuable contributions.

The model presented in this paper is a synthesis of different strains of the literature, which stress the importance of (i) consistent, explicit balance sheet accounting, (ii) endogenous linkages between the macroeconomy and the financial sector, including endogenous feedback loops and (iii) nonlinearities.

A seminal work in this area comes from Benes et al. (2014a, 2014b) who describe a model developed at the IMF to support macro-financial and macroprudential policy analysis (MAPMOD). The model features banks and their balance sheets that play fundamental roles. Globally non-linear version of the model allows capturing basic stylized facts of both pre-crisis and crisis phases of financial cycles. In the opposite, the conventional linearized DSGE models are not very useful as they, by construction, do not capture the effects of nonlinearities and ignore the special role played by banks and macro-financial feedbacks in contributing to vulnerabilities (Borio (2014)). The MAPMOD has been a valuable source of insight on the necessary features of a good macroprudential model and is able to shed light on many important phenomena. However, due to its complexity the MAPMOD is too large to be operable in policy-making framework. We therefore see the MAPMOD as an important stepping stone and the key inspiration for the model presented in this paper[4].The wider literature also recognizes the necessity of explicit balance sheet accounting and linking the performance of assets on bank balance sheets to macroeconomic developments. Drehmann et al. (2009) developed a framework to measure the integrated impact of credit and interest rate risks, considering the repricing characteristics of assets, liabilities and off-balance sheet items. The contribution of the paper is that it explicitly ensures that the balance sheet of the banking sector balances at any point in time, something which the previous stress testing models did not always follow. The framework also incorporates projection of default probabilities conditional on macroeconomic forecast in each quarter over a three years horizon. More recently, Miess et al. (2019) created a stock-flow consistent model enabling coherently incorporating the institutional structure of a complex modern financial sector and the corresponding potential financial instability. It allows to explain the build-up of asset price bubbles and to evaluate macro-prudential regulations with respect to their effects on economic growth and the business cycle. They include institutional details by explicitly accounting for the balance sheet composition of aggregated macroeconomic agents. A more detailed, applied contribution comes from Gaffney, Kelly and McCann (2019) who estimate losses from residential mortgage loans using a transition-based loan-level probability model, estimated on Irish data. The model uses macroeconomic and other inputs (LTV) to estimate loans' key performance characteristics such as probability of default and loss-given-default.

Jobst, Ong and Schmieder (2017) provide an overview of the approach to the macroprudential Liquidity Stress Testing in the Financial Sector Assessment Program (FSAP) for countries with systemically important financial sectors. Adrian, Morsink and Schumacher (2020) provide an overview of the current IMF stress-testing methodology.

The importance of endogenous macro-financial feedback effects was investigated by several papers. Krznar and Matheson (2017), identified the macro-feedback effects as the key missing component for more effective macroprudential stress testing. Their framework facilitates the analysis of both the direct effects of macroeconomic shocks on the solvency of individual banks and feedback effects that allow for the amplification and propagation of shocks that can result from bank deleveraging and credit crunches. Their stress tests also rely on exogenous macroeconomic scenarios, behavioral ad-hoc assumptions related to individual banks and reduced-form relationships that map the macroeconomic scenarios into various forms of risks.

The topic of non-linearities in macro-financial models was surveyed by Dou et al (2021), who also point to the potential pitfalls of using local solution methods which approximate the nonlinear dynamics by a local-linearization of the system

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[4] *The model described in this paper follows Benes (2023, forthcoming).*

around a chosen point. The authors highlight that using local solutions can lead to an important loss of precision and biased impulse-response dynamics.

The topic of monetary and macroprudential policy coordination has also received a fair share of attention. Angelini et al (2012) developed a DSGE model with the banking sector, focusing on monetary and macroprudential policy interaction. They also normatively discuss that adequate models should include the financial externalities and proxies for the systemic risk that macroprudential policies are intended to cope with; they should be complex enough to allow for meaningful interaction between monetary and macroprudential policy; and they should probably feature an important role for nonlinearities.

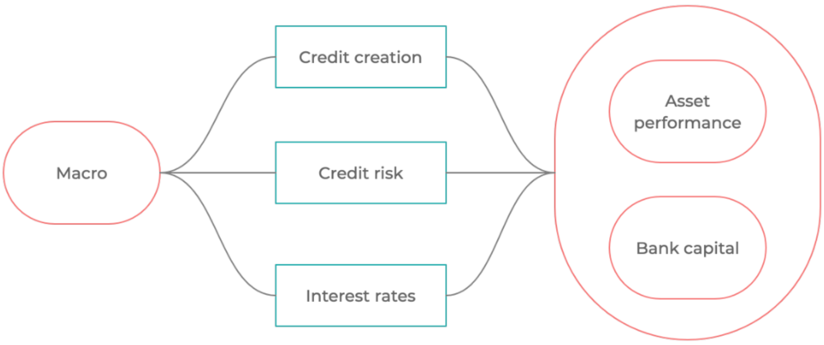
Engelmann (2020) examines the formula commonly used to calculate provisions for expected credit losses by banks reporting under IFRS standards. He presents an exact calculation based on discounted cash flows, which motivates the formulation used in the model presented in this paper.

3. General description of the model

This section provides a bird's eye view of the model, discussing the key features which are described in detail further.

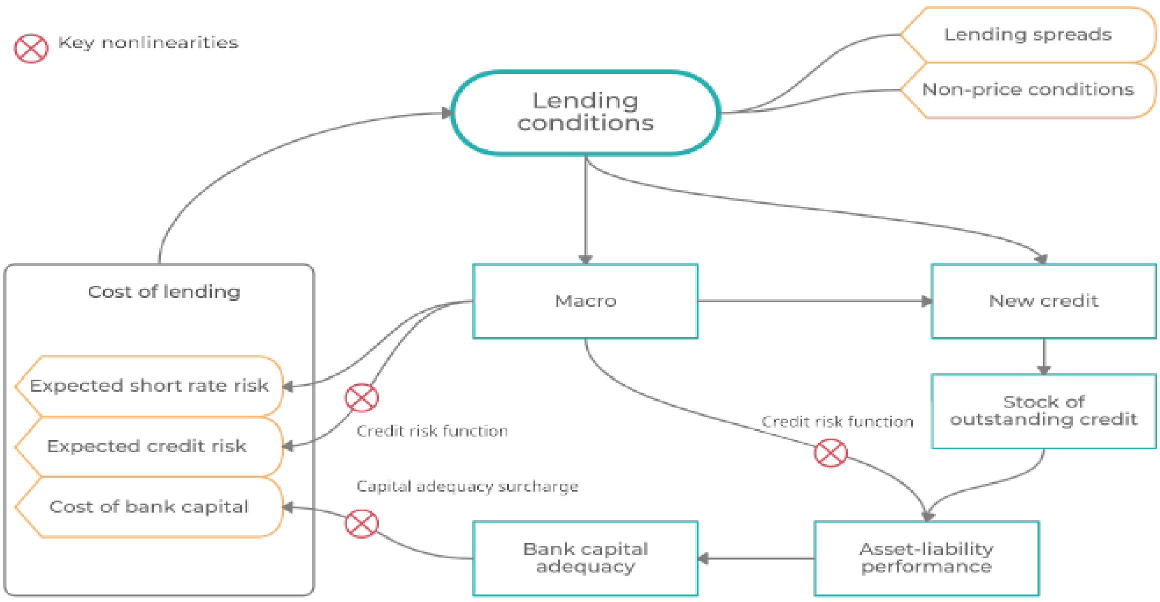
3.1 Model structure

Figure 1: Model Structure



The model structure consists of six basic modules as shown in Figure 1. The modules are interconnected through a set of simultaneous equations, giving rise to a set of dependencies of which the key ones are depicted in Figure 2.

Figure 2: Module interconnections



The key variable by which the financial sector influences the real economy are the lending conditions. The lending conditions influence both the macroeconomic performance (output growth) and the issuance of new credit. The issuance of new credit is therefore determined by demand factors (macroeconomic conditions) and supply factors (lending conditions). The stock of outstanding loans in the bank balance sheet is accumulated from the new credit minus the credit that either matures or is nonperforming and is written off during the period.

Macroeconomic conditions and a debt overhang over (unobservable) sustainable level of credit / debt (akin to the usual "credit gap" measure) jointly determine the performance of loans described by the period portfolio default rates. Poor economic conditions, in conjunction with excessive debt burden, increase the default rates, which translates into a higher share of non-performing loans and declining bank profitability. A key model non-linearity relates the default rate in the economy to the macroeconomic conditions, as shown in Figure 2. In "normal times" when the economy is close to equilibrium, the elasticity of default rates to macroeconomic conditions is small and aggregate loan portfolio performance is largely unaffected by changes in macroeconomic conditions. However, as the macroeconomic conditions worsen, the elasticity increases, and loan portfolio performance deteriorates quickly. The profitability of banks, in turn, determines the bank capital position measured by the capital adequacy ratio (CAR). This nonlinearity is of paramount importance for macroprudential modeling.

The key variable determining bank behavior is the CAR. The model assumes that banks hold an "excess" CAR above the regulatory minimum CAR (the minimum includes also various buffers, e.g., counter-cyclical buffer) to safeguard against unforeseeable adverse shocks which could lower CAR below minimum, thus triggering regulatory action which is costly for the banks. The difference between the actual CAR and the optimum desired CAR, which composes of the minimum CAR and excess CAR held for prudential reasons, is the key input into bank decision-making.

3.2 Lending conditions

Banks decide on the lending conditions based on:

i. Autonomous profit margin which represents a target level of profitability that banks aim to achieve.
ii. The expected credit risk. Banks set lending conditions so as to achieve the desired rate of return, taking into account expected credit risk. Weaker macroeconomic conditions lead to higher expected credit risk, which prompts banks to tighten lending conditions.

iii. Expected policy rate path. Banks also set the level of lending conditions based on the anticipated path of the policy rates as determined by the central bank. The policy rate is important as it largely determines the cost of financing bank liabilities.

iv. Bank capital position. Weaker capital position prompts banks to tighten lending conditions in order to increase rate of return on unit of loan but also to reduce the amount of newly extended credit

Lending conditions are decomposed into two components: Price lending conditions and non-price lending conditions. Banks may tighten lending conditions by raising the interest rate on loans (the price component), or by making the conditions of access to credit more restrictive through various non-price requirements such as requesting proof of income, requesting co-signer on the loan, and other. Empirically, the level of lending rates alone is a poor predictor of credit issuance while the role of non-price component is empirically large, as the observed interest on loans doesn't change enough to plausibly explain the changes in issuance of the new credit. We therefore introduce a shadow lending rate, which captures the joint effect of the price and non-price component of the lending conditions. The shadow lending rate is the true measure of overall lending conditions and as such affects the real economic activity and issuance of new credit. We also explicitly track the price component of the lending rate as that determines bank income.

Summing up, the model simulates the macro-financial linkages between banks and the economy. Macroeconomic conditions influence bank decision making both directly through the expected credit risk, and indirectly through the level of bank capital. The real economy, in turn, is affected by bank decision to tighten / ease lending conditions.

In general, macroprudential policy models are not intended to be used for forecasting purposes as the forecast represents the most likely scenario. Macroprudential policy is however concerned with preventing the downside scenario with severe macroeconomic costs, which rarely is identical to the baseline. Economic forecasts are generally used as input into these models and constitute the baseline (or most likely) scenario against which crisis or risk scenarios are assessed. This model can therefore be connected to the existing Bank's economic forecasting framework to conduct simulation exercises related to financial stability and the banking sector which are derived from Bank baseline forecast.

3.3 Limitations

A limitation of this model relative to other DSGE models for financial stability in the literature is that the model does not explicitly incorporate a central bank reaction function for macroprudential policy. In models built for monetary policy analysis, this reaction function is most often in the form of a Taylor rule where the target and instrument of monetary policy is clearly stated (typically price stability defined as low and stable inflation with the policy rate as the instrument). On the other hand, there is still no consensus on the precise, measurable target of macroprudential policy and the hierarchy of macroprudential policy instruments. Indeed, the instruments used vary from country to country and from period to period.

Our approach is therefore to not state an explicit macroprudential policy function, but to allow for a range of macroprudential policy instruments to be included as one-off interventions in simulations. For example, in the model, the counter-cyclical conservation buffer (CCYB) is modeled as an exogenous autoregressive process and is not expressed as a function of macroeconomic variables (such as the output gap or the credit gap). We can nevertheless examine the consequences of the changes in the CCYB by exogenously changing it in a simulation. Nevertheless, for purposes of one-off simulations, it is possible to incorporate a particular macroprudential policy rule. For example, an increase in the credit gap would automatically trigger an increase in a certain capital buffer. In the current state of the model, the operator introduces an exogenous shock to the macroprudential instruments to assess their effects, but these rules are not introduced into the model endogenously.

Furthermore, we note that in the current version of our model, we limit the available set of policy instruments to

- Capital-based instruments: Capital Ratio and Countercyclical Capital Buffers (CCB)
- Liquidity-based instrument: Liquidity Coverage Ratio (LCR)
- Asset-side instruments: Leverage ratio and real estate prices

However, the structural nature of the model allows us to represent a wide range of additional policy instruments, such as systemic risk buffer (SyRB), Net Stable Funding Ratio (NSFR), debt-to-income (DTI) and loan-to-value ratios (LTV).

Finally, it is important to point that the current model considers many assumptions, including the calibration of nonlinearities and unobserved trends. While this type of assumption is quite common for a classical macroeconomic model, the degree of uncertainty here is much greater because we are dealing with rare events. Our model must deal with the lack of data related to financial crises, which fortunately remain rather rare. This is especially true in case of the Moroccan economy where the available data covers scarcely one financial cycle. Indeed, normal periods are not indicative of the behavior of the economy and the financial sector in case of a crisis. We therefore treat the model and its quantitative outputs with an appropriate degree of uncertainty.

4. Model description

This section provides a general, but not thorough, discussion of the main equations of the model. The model has a modular structure and can be easily expanded.

4.1 Aggregate bank balance sheet

The model features an explicit, simplified representation of an aggregate balance sheet of the banking sector. The unit of all the assets and liabilities is the Moroccan Dirhams (MAD).

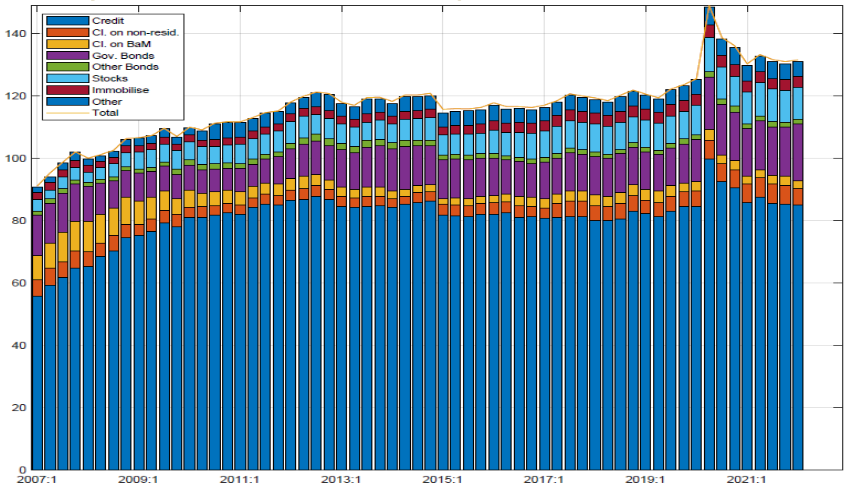
Table 1: Aggregate bank balance sheet

Assets	Liabilities
Net bank loans	Debt and deposits
(+) Gross bank loans	Capital
(-) Provisions for liabilities and charges	
Other assets	

The items on the balance sheet interact with the rest of the model including the macroeconomy. Although the primary focus is on description of the dynamics of the bank loan portfolio, we also model the impact of the remaining assets which in Morocco account for about one third of total bank assets. These non-loan assets are classified as:

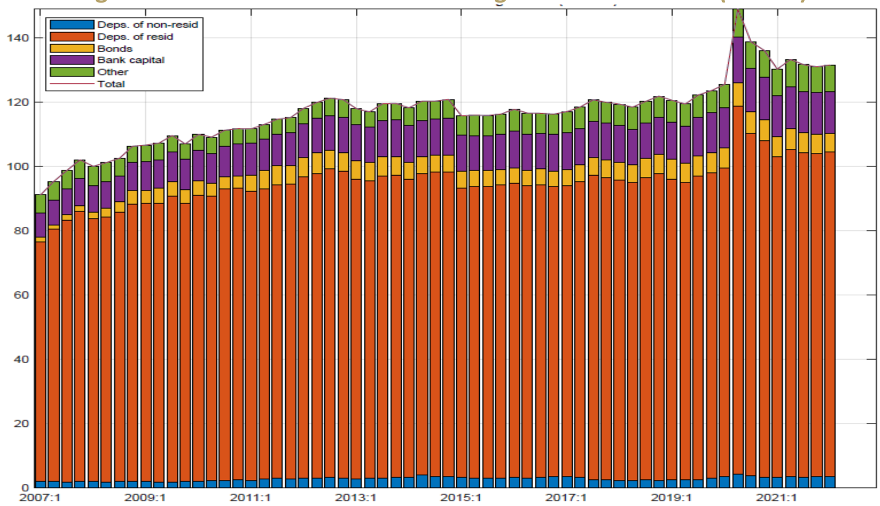
- Government bonds
- Risky assets - stocks, corporate bonds, etc.
- Other assets

Figure 3: Total assets of the banking sector in Morocco (% GDP)



In the liabilities the model distinguishes between equity (bank capital) and non-equity liabilities (debt and deposits). The majority of non-equity liabilities are deposits, as visible in Figure 4.

Figure 4: Total liabilities of the banking sector in Morocco (% GDP)



4.2 Loan portfolio

The loan portfolio account for about two thirds of all assets of banks in Morocco and drives a large part of the model dynamics by linking the performance and dynamics of the loan portfolio to the real economy.

A life cycle of a representative loan, from origination to repayment (or default), is modeled as follows: In each period, a portion θ of the outstanding loan value l_t is paid back, along with interest. The inverse of the parameter θ therefore determines the average maturity of the loan portfolio. In the absence of credit risk, the stock of loans evolves simply as:

$$L_t = (1-\theta)L_{t-1} + L_t^A$$

where L_t^A represents the gross production of new loans as the model progresses in time from "closing" balance rolled over from previous time t-1 to the "opening" balance at time t. Consequently, the cash flow generated by a representative loan follows the following dynamic:

Table 2: Example of a representative loan life cycle

	Origination	T=0	T=1	…
Value at end of period	L	$(1-\theta)$	$(1-\theta)^2L$	
Repayment		θL	$\theta(1-\theta)L$	
Interests		r_0L	$r_1(1-\theta)L$	
Cash-flow total		$(\theta+r_0)$	$(\theta+r_1)(1-\theta)L$	

In each period t, a proportion θ of the previous period's credit is repaid. A variable gross interest rate r_t is applied to the amount of credit valued at the end of the previous period to calculate the interest payment. The cash flow generated by the credit portfolio is the sum of the interest incurred and the principal repaid.

Part of the credit can become non-performing through a mechanism explained further. We again keep explicit account of values of performing and non-performing loans:

$$L_t = L_{P,t} + L_{N,t}$$

Where $L_{P,t}$ represents performing loans and $L_{N,t}$ represents non-performing loans.

Banks create a stock of allowances[5] against credit losses, which is also accounted for in the aggregate bank balance sheet. The amount of provisions each period can be calculated according to two approaches:

a) Forward-looking, expected-credit-loss-based approach consistent with IFRS9 methodology allowances are calculated as the sum of future expected credit losses.
b) Backward-looking, incurred-credit-loss-based approach in which allowances correspond to observed credit (non)performance and are equal to a fixed share of the NPLs. The model currently uses this approach as it corresponds to the current accounting standards in Morocco, but a switch to the IFRS9-consistent approach is very simple.

Given the default rate q_t prevailing in the economy at time t (explained below), the dynamics of performing loans is governed by:

$$L_{P,t} = (1-q_t)L_{P,t-1},$$

The dynamics of non-performing loans depends also on the Loss Given Default rate λ, where 1-λ represents the recovery rate – the part of the loan which remains recoverable even after credit event. As a result, the recovery buffer of non-performing loans follows the following recursive dynamics:

$$L_{NC,t} = L_{NC,t-1} + (1-\lambda)q_tL_{p,t-1}.$$

The write-off buffer dynamics is given by:

$$L_{NW,t} = L_{NW,t-1} + \lambda q_tL_{p,t-1}.$$

For provisions, we note a_t the stock of provisions as it appears on the balance sheet and a_t^{Δ} the flow of provisions as it appears in bank income statement. Given the write-offs w_t, the dynamics of allowances are as follows:

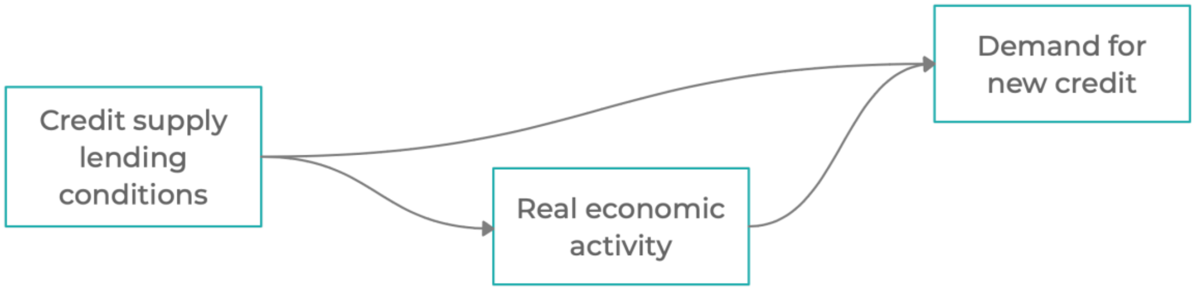
$$a_t = a_{t-1} - w_t + a_t^{\Delta}$$

[5] *We distinguish between provisions as a flow variable measured per period and allowances as a stock variable in the balance sheet. The process of creation of new allowances is called provisioning.*

4.2.1 Production of loans

The production of new loans depends on supply factors (lending conditions) and demand factors (real economic activity). Motivated by insights from research into DSGE models, we consider the following structure:

Figure 5: Interconnections between real economy and Credit supply and demand



Recall that lending conditions are represented by the shadow lending rate which affects both the credit production as well as real economic activity. The introduction of the shadow lending rate is motivated by empirical studies that show that banks might reflect their perception of risk more in non-price lending conditions rather than solely in their lending rates. In other words, the shadow rate is more volatile than observed lending rates and better explains the production of new loans.

The theoretical motivation for credit demand equations are built on the understanding that credit creation is also money creation and money serves transactions in the economy. These transactions can be related to newly created value, approximated by the value added (nominal GDP), or to trade with already existing assets (e.g., a sale of a house built in the past). Each unit of currency can take part in several transactions per year (money velocity). We therefore use the following equation:

$$l_t = ivy_t . trn_t e^{\epsilon_{l\Delta,t}}$$

where trn_t is the value of transactions in the economy that require bank credit financing and ivy_t is the inverse credit velocity. This equation thus links economic activity to credit creation.

The amount of period transactions depends on the current GDP and asset prices, approximated here by the discounted sum of future nominal GDP streams:

$$trn_t = py_t y_t + c_{trn} py_t y_t^{fws}$$

Where $py_t y_t$is real GDP (py_t is the GDP deflator) and $c_{trn} py_t y_t^{fws}$ is the volume of buy/sell activity in existing assets. $y_t^{fws}$is the present value of future expected GDP streams, following the asset pricing theory where the value of an asset is equal to the discounted sum of future income generated by that asset. The inclusion of the expected future GDP streams is helpful to explain many observed facts about credit creation, but it also allows to simulate events such as bubbles / credit gluts where expectations of future income lead to a fast increase in credit but eventually turn out to be overly optimistic. The revision of expectations then leads to deleveraging with adverse effects on the real economy and credit performance.

Beyond macroeconomic factors, credit creation is also a function of lending conditions tightness, as well as the credit overhang above a sustainable level. These factors are captured by the inverse credit velocity ivy_t.

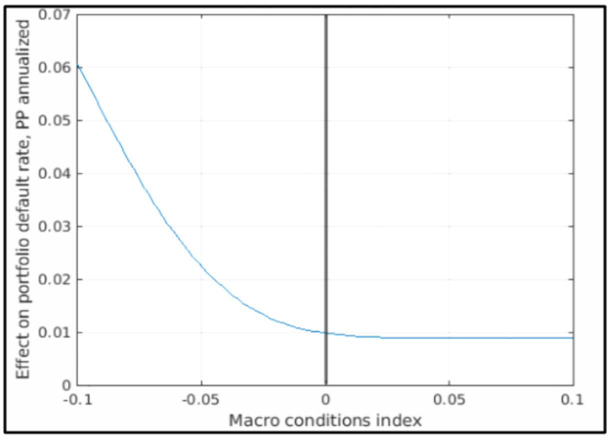
4.2.2 Credit risk

The interaction of the real and financial spheres is modeled through a credit risk function that relates the macroeconomic conditions to the default rate on bank loans. The credit risk function takes the following form:

$$q_t = \alpha + (\beta - \alpha)\left[\frac{1}{1 + exp\left(\frac{-z_t - \mu}{\sigma}\right)}\right]^{exp\vartheta}$$

Where μ, σ, and ϑ control the shape of the curve, α and β are bounds on the default rate, and z is an index of macroeconomic conditions. Through this function, a shock to macroeconomic conditions affects the default rate in a nonlinear fashion.

Figure 6: Credit risk function



Empirical estimation of this function is not feasible, as there are usually only one or two periods of sufficient macroeconomic stress in recent history which carry information about the left tail of the curve. We therefore calibrate the function and use several simulation exercises to ensure the calibration yields sensible results.

The function is nonlinear and highly malleable and able to describe various kinds of relationships between the real economy and credit default rate. The shape of the curve is such that when the economy (output gap) is close to equilibrium, a slight variation in economic conditions have little impact on the default rate. However, as the economic conditions worsen, the slope of the curve steepens, representing the idea that in crisis times even minor changes in economic conditions can have a significant, non-linear impact. Macroprudential policy is chiefly concerned with these tail events with low probability but high impact.

$$z_t = (logy_t - log\overline{y_t}) - c_1^z\left(\left[\frac{l}{4pyfwy}\right]_t - \overline{\left[\frac{l}{4pyfwy}\right]_t}\right) - c_2^z\left(\frac{\left[\frac{repi}{py}\right]_t - \left[\frac{repi}{py}\right]_{t-8}}{\left[\frac{repi}{py}\right]_{t-8}}\right)$$

The macroeconomic conditions index is composed of the output gap $(logy_t - log\overline{y_t})$, the credit gap $\left[\frac{l}{4pyfwy}\right]_t - \overline{\left[\frac{l}{4pyfwy}\right]_t}$ and the deflated real estate price index gap $\left(\frac{\left[\frac{repi}{py}\right]_t - \left[\frac{repi}{py}\right]_{t-8}}{\left[\frac{repi}{py}\right]_{t-8}}\right)$.

The credit gap, which represents the deviation of credit-to-GDP ratio from its trend, is expressed relative to the future expected GDP. The term $\overline{\left[\frac{l}{4pyfwy}\right]_t}$ is a measure of the sustainable ratio of credit to GDP. This equation links the credit default rates to expectations of future GDP. fwy_t is the discounted sum of future expected GDP. The discount factor depends on the hypothetical (unobservable) level of lending rates that would cover all lending costs (see section 4.3) and (expected) risks:

$$fwy_t = (1-\frac{1}{c_0})[y_t + \frac{1}{(c_0 + c_1 rl_t^{\Delta full}) y_{ss}^{roc}} y_{t+1} + \cdots]$$

If economic agents are optimistic about future growth and therefore their future income, then the fwy term increases which improves the economic conditions index, lowers the debt relative to expected income, and improves credit performance. Conversely, a deterioration in agents' expectations, coupled with high levels of credit, reduces the index of macroeconomic conditions. This feature also allows us to endogenously simulate an unsustainable buildup of credit which is accompanied by favorably low default rates based on overly optimistic expectations about future, with subsequent reversal, deleveraging, and crisis.

4.3 Lending rate dynamics

4.3.1 Lending rate decomposition

The lending conditions are built from several components. We start with the base rate representing the desired rate of return on bank credit. This rate would be offered to a hypothetical borrower with zero credit risk

$$rl_t^{base} = rs_t + rl_t^{apm}$$

Where rs_t is the policy rate (as a benchmark that sets the cost of liabilities) and rl_t^{apm} is the autonomous profit margin representing the desired interest margin of the bank. Credit risk premium is added on top of the base rate based on the expected credit risk profile based on the information known at the time of credit issuance.

The hypothetical lending rate covering the full expected credit risk is given by

$$\mathrm{rl}_t^{\Delta \mathrm{full1}} = (1-\psi_1)\left(\left[\frac{1+rl_t^{\Delta base}}{1-\lambda \mathrm{q}_{t+1}}\right] + \psi_1 \left[\frac{1+rl_{t+1}^{\Delta base}}{1-\lambda \mathrm{q}_{t+2}}\right] + {\psi_1}^2 \left[\frac{1+rl_{t+1}^{\Delta base}}{1-\lambda \mathrm{q}_{t+2}}\right] + \cdots\right)$$

Where ψ_1 is a discount factor. An increase in the expected losses on credit portfolios $\lambda \mathrm{q}_{t+1}, \lambda \mathrm{q}_{t+2}$ … raises the full lending rate $\mathrm{rl}_t^{\mathrm{full}}$.

In a similar manner, the cost of lending must reflect the forward lending cost of bank capital. The rate covering the cost of bank capital is given by

$$\mathrm{rl}_t^{\Delta \mathrm{full2}} = (1-\psi_2)\left((1+rx_t\ ) + \psi_2(1+rx_{t+1}) + {\psi^2}_2(1+rx_{t+2}) + \cdots\right) + \varepsilon_t^{rl\Delta full,2}$$

Where ψ_2 is a discount factor (see section 4.3.2 for a detailed explanation of the regulatory surcharge rx_t).

Overall, the hypothetical lending rate reflecting all costs is given by

$$1 + rl_t^{\Delta full} = (1+\mathrm{rl}_t^{\Delta \mathrm{full1}})(1+\mathrm{rl}_t^{\Delta \mathrm{full2}})$$

It is empirically difficult to match changes in observed lending rates to changes in the volume of new credit. The data commonly shows little volatility in lending rates that can only be squared with observed changes in new credit volumes by assuming implausibly high elasticity. This stylized fact can be explained by the non-price lending conditions: additional non-price costs that banks impose on borrowers when they wish to tighten lending conditions. The non-price lending conditions can encompass LTV ratios, collateral requirements, requirements to obtain co-signature on the loan, etc. The literature on non-price lending conditions suggests that much of the variations in new credit volume can be attribute to changes in these conditions.

We reflect the role of non-price lending conditions by splitting the hypothetical full-cost rate $rl_t^{\Delta full}$ into a price component $\mathrm{rl}_\mathrm{t}^{\Delta}$, i.e. the actually observed new lending rate and non-price conditions ($rl_t^{\Delta full} - \mathrm{rl}_\mathrm{t}^{\Delta}$) measured by an interest rate equivalent (passed on to borrowers). The extraction of the price component is based on the spread over the base rate. Parameter c_1 controls what share of risk is reflected in the price components as opposed to the non-price conditions:

$$\mathrm{rl}_\mathrm{t}^{\Delta} = \mathrm{rl}_\mathrm{t}^{\Delta\mathrm{base}} + \mathrm{c}_1\left(\mathrm{rl}_\mathrm{t}^{\Delta\mathrm{full}} - \mathrm{rl}_\mathrm{t}^{\mathrm{base}}\right) + (1 - \mathrm{c}_1)\left(\mathrm{rl}_\mathrm{ss}^{\Delta\mathrm{full}} - \mathrm{rl}_\mathrm{ss}^{\Delta\mathrm{base}}\right)$$

When $\mathrm{c}_1 = 0$, $\mathrm{rl}_\mathrm{t}^{\Delta} = \mathrm{rl}_\mathrm{ss}^{\Delta\mathrm{full}}$ which means that banks do not adjust the price component of the lending rate to a rise in credit risk, and all the credit risk is absorbed into the non price component.

When $\mathrm{c}_1 = 1, \mathrm{rl}_\mathrm{t}^{\Delta} = \mathrm{rl}_\mathrm{t}^{\Delta\mathrm{full}}$. In this case, banks fully reflect a rise in credit risk into the price component of lending conditions, and leave the non price component unchanged.

The hypothetical full-cost rate $\mathrm{rl}_\mathrm{t}^{\Delta\mathrm{full}}$ enters the aggregate demand and credit demand equations,

as it represents the true cost of credit for borrowers. The observed lending rate $\mathrm{rl}_\mathrm{t}^{\Delta}$ enters the bank profits calculation.

4.3.2 Regulatory surcharge

As for the regulatory surcharge rx_t, a decrease in regulatory capital induces a surcharge on the lending rate on the part of the banks, allowing them to restore capital to comfortable levels. The regulatory surcharge is a function of the capital shortfall measured as the differential between the current CAR of the bank car_t and the regulatory minimum $car_t{}^{min}$.

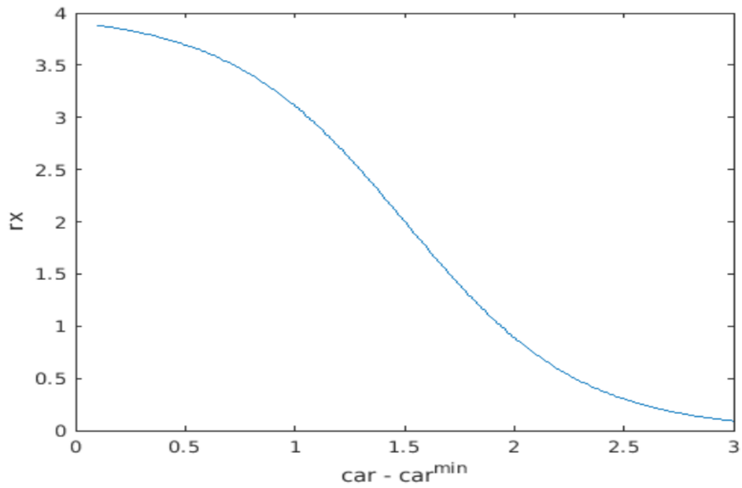
The closer the actual CAR approaches regulatory minimum, the more likely it becomes that the bank might experience unforeseen negative shock which would push the CAR below minimum, triggering costly regulatory action. To avoid this, the bank might opt to raise more capital, but that incurs costs to bank owners. In practice, banks often respond by tightening lending conditions to shrink their balance sheet. While this behavior is sensible from the standpoint of an individual bank, it might cause economic downturn if pursued by the whole banking sector at the same time, thus in turn worsening the credit performance and inducing a negative feedback loop.

We link the capital risk surcharge to capital shortfall via a non-linear function depicted below, again pursuing the idea that changes of capital position in “normal times” have negligible effect on bank lending conditions, but in the time of crisis the banks become much more sensitive and can tighten lending conditions sharply.

$$rx_t = \underline{rx} + \left(\overline{rx} - \underline{rx}\right)\left[1 + e^{\frac{car_t - car_t{}^{min} - \mu^{rx}}{\sigma^{rx}}}\right]$$

This function is represented in the following graph:

Figure 7: Regulatory surcharge on lending rates



4.4 Equity

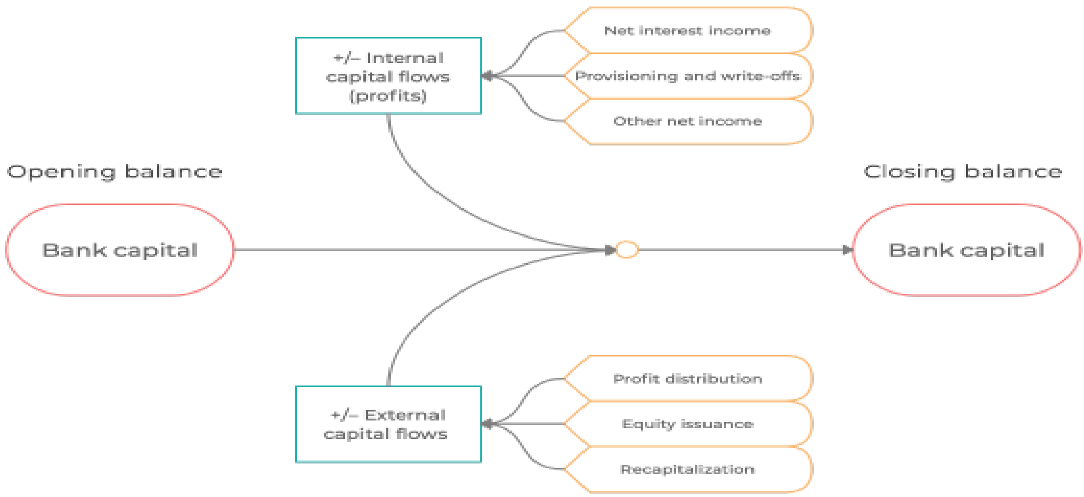
4.4.1 Bank capital

Bank capital is explicitly tracked on the balance sheet and used to keep track of bank capital position as expressed by the CAR. Banks can accumulate capital from internal (net income) or external flows as described Figure 8. External flows are usually negative in the form of dividends. The dynamics of bank capital take the form:

$$bk_t = bk_{t-1} + prof_t + xcf_t,$$

where bk_t is bank capital, $prof_t$is net income and xcf_t is external capital flow.

Figure 8 : Bank capital flows



4.4.2 Bank profit

The bank net profit/loss is calculated by accounting for all the following items on the balance sheet:

- Components of period profit/loss
- Interest income on loans (by segments)
- Income on other assets

- Other income and expense (proxy for fees, commissions, operating costs, etc.) as a fixed share of total bank assets
- Interest expense on non-equity liabilities
- Provisioning and write-offs

4.4.3 Bank capital position

The regulatory capital is obtained by:

$$regk_t = \left[\frac{regk}{bk}\right] bk_t$$

where $\left[\frac{regk}{bk}\right]$ is a term that allows for potential difference between the capital as introduced on the bank balance sheet and the regulatory capital as calculated by bank supervision authorities. The CAR is calculated as follows:

$$car_t = \frac{regk_t}{riskw_t l_t}$$

where $riskw_t l_t$ represents average risk weight, an exogenous variable in the model.

Banks want to hold a management buffer above the minimum level of regulatory capital. Their goal is to hold a level of capital car_t^{tar} exceeding the regulatory minimum car_t^{min} by a management buffer car_t^{exc} :

$$car_t^{tar} = car_t^{min} + car_t^{exc}$$

4.4.4 External capital flows

External capital flows can be positive (capital injections) but are usually negative as in the form of dividend payments. The steady-state value of the external capital flows is determined by the steady-state growth rate of the bank capital and steady-state bank net income. The banks in the model retain as much earnings as necessary to maintain a comfortable capital position, paying out the rest. The model equation links the external capital flows to capital position – weak capital position induces the banks to reduce dividends or potentially inject additional capital, and vice versa:

$$(1 - c_{xcf})\left(\left[\frac{xcf}{bk}\right]_t - \left[\frac{xcf}{bk}\right]_{ss}\right) - c_{xcf}(car_t - car_t{}^{tar}) = 0$$

The parameter c_{xcf} controls the degree of responsiveness of external capital flows to bank capital position. When $c_{xcf} \to 1$, the bank fully adjusts its dividend distribution to consistently maintain the level of CAR at the target level. When $c_{xcf} \to 0$, external capital flows remain stationary at the steady-state level and are not adjusted in response to changes in CAR.

4.5 Other main features of the model

4.5.1 Loan segmentation

The model also allows bank lending to be segmented into K categories, e.g., consumer, real estate, etc. The equations describing the dynamics of credit volumes, interest rates, and other variables for each category remain as described above, but the parameters describing the characteristics of the loans in these segments and the non-linear functions may vary from one category to another. This feature is currently not implemented in the model due to a lack of necessary data.

4.5.2 The real economy

The macroeconomic block follows the standard blueprint of the Moroccan Quarterly Projection Model (MQPM), used by Bank Al-Maghrib for monetary policy analysis and forecast. The only deviation from the standard blueprint (Benlamine et al. (2018)) is in the IS Curve. In our model, we allow for the shadow lending rate gap $\hat{rl}_t^{full}$ to impact the output gap, in addition to real interest rate gap.

4.5.3 Delta-method for scenario building

We implement model-based scenarios on top of the baseline using the delta method. Baseline projections from an extraneous source (monetary policy forecasts) are used as a starting point. These baseline projections are transformed into a sequence of shocks. The scenarios are integrated on top of these baseline shocks to the model, in the form of shocks, exogenized paths, or changes in steady state assumptions.

5. Use cases

5.1 Macroeconomic impact of an increase in equity capital

This simulation evaluates the economic and financial impact of an increase in capital according to three scenarios. The first simulates an immediate implementation by the banks of a 2.5pp increase in minimum CAR ratio ("Immediate" in yellow), the second a fast-track implementation (in red) and the last a slow track implementation (in blue).

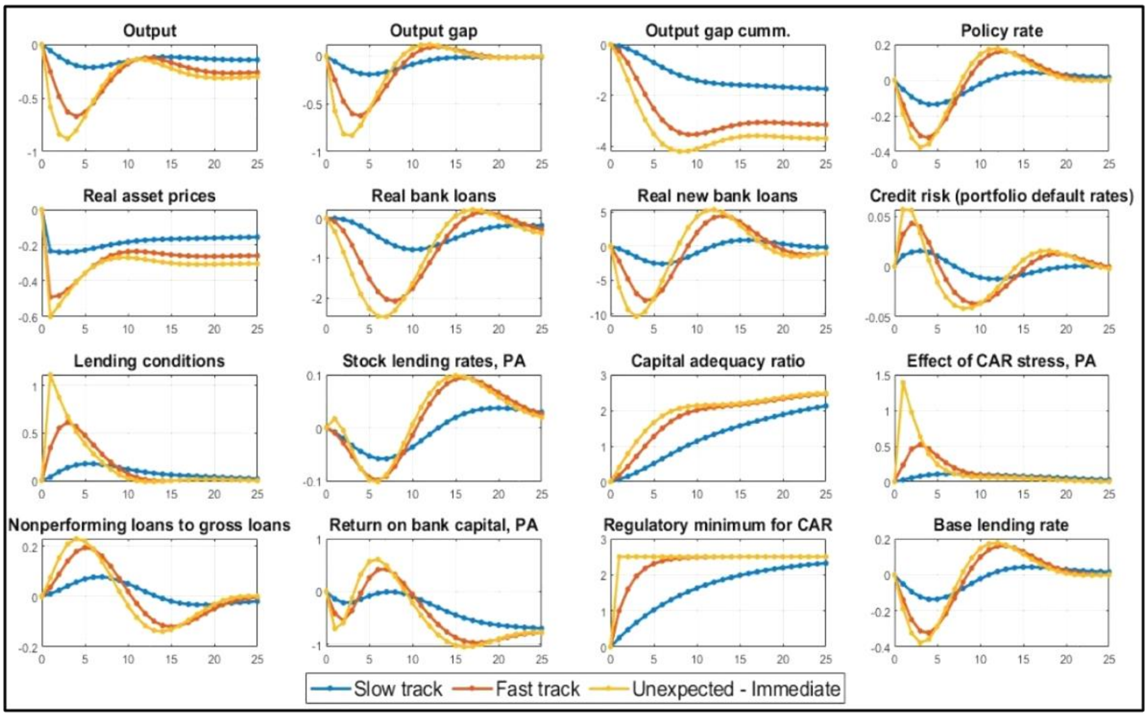
Banks maintain a precautionary buffer above the minimum regulatory capital. The increase in the minimum regulatory capital squeezes the banks' capital buffer. To rebuild that capital buffer, banks tighten lending conditions to generate more income and shrink bank balance sheet.

Under the first scenario (Immediate) in yellow, the minimum required capital ratio increases almost instantly by 2.5pp. The equity capital of the banks falls immediately below the precautionary buffer, which leads them to increase the regulatory surcharge on lending rates. Depending on the size of the capital shortfall, the increase in the regulatory minimum capital requirement might imply tightening of lending conditions based on the non-linear function presented in section 3.6. Tightening lending conditions negatively impact the volume of new loans, which is falling rapidly and significantly (-10%) in the short term, as well as real economic activity. Banks are seeing their credit volume decrease as well as their profitability due to the reduction of their balance sheet and the increase in their equity. However, banks are achieving the expected objective of a rapid increase in the regulatory ratio as shown in the chart. At the level of the real economy, the shock results in lower growth and real asset prices.

For the other two scenarios, the direction of the responses remains similar, but the magnitudes are less pronounced for Fast-track and much less for Slow-track with a lower cost to the economy. Indeed, as shown in the graph, the cumulative output gap, which represents a proxy for the cumulative cost to the economy, appears to be twice as high under the yellow scenario (Immediate) compared to the blue one (Slow-track).

This exercise shows that by preparing the banks and informing them sufficiently in advance of an increase in the capital ratio, we allow them to anticipate and spread out their decisions over time to achieve the regulatory objective, thus limiting the cost to the real economy.

Figure 9: Impact of a capital increase with monetary policy



5.2 *The role of capital flows sensitivity to capital buffers building requirement*

This simulation underlines the macroeconomic and banking system reaction to capital buffers building by increasing the long-run regulatory CAR minimum by 2.5pp. The three simulations presented below are based on the three simulations introduced in the previous subsection: slow track (Figure 10), fast track (Figure 11) and immediate increase (Figure 12). At first glance, this simulation seems similar to the first one (section 4.1). However, it is different in the way that it highlights the role played by the external capital flows sensitivity to profits. For each simulation, we vary the flexibility of the external capital flows: "Baseline" is the baseline model calibration, "Sluggish xcf" implies that external capital flows will remain almost unchanged, and "Immediate recapitalization" implies that the required additional capital is immediately provided, for example by bank owners.

The external capital flows are made up of i) profit distribution, ii) equity issuance and iii) recapitalization. And the sensitivity of the relationship between those capital flows and the current profit/loss is set through the coefficient c_{xcf} (cf. section 3.7.3).

When this coefficient equals 0, it means that external capital flows do not respond to fluctuations in capital adequacy ratio and banks owners do not adjust external flows (e.g., dividends) based on the current profit/loss at all. In the opposite, when the c_{xcf} coefficient is 1, it means that external capital flows always bring capital adequacy ratio to its target level and Bank owners adjust external flows (e.g., cut dividends, add capital) to always ensure a CAR level equaling the long-run regulatory CAR minimum.

Our baseline scenario uses a c_{xcf} coefficient of 0.5 while the two other scenarios are based on coefficients of 0.25 for the "sluggish" scenario and 1 for the "Immediate recapitalization" scenario.

In all simulations (immediate, fast and slow CAR increase), the "Immediate recapitalization" scenario (+1) shows the best performance as it keeps the economy away from perturbations. In fact, as banks adjust their external flows instantly to the regulatory minimum for CAR, there is no risk surcharge from the CAR differential and the lending conditions remain stable.

Figure 10: Simulation results for Gradual build-up of 2.5pp capital buffer

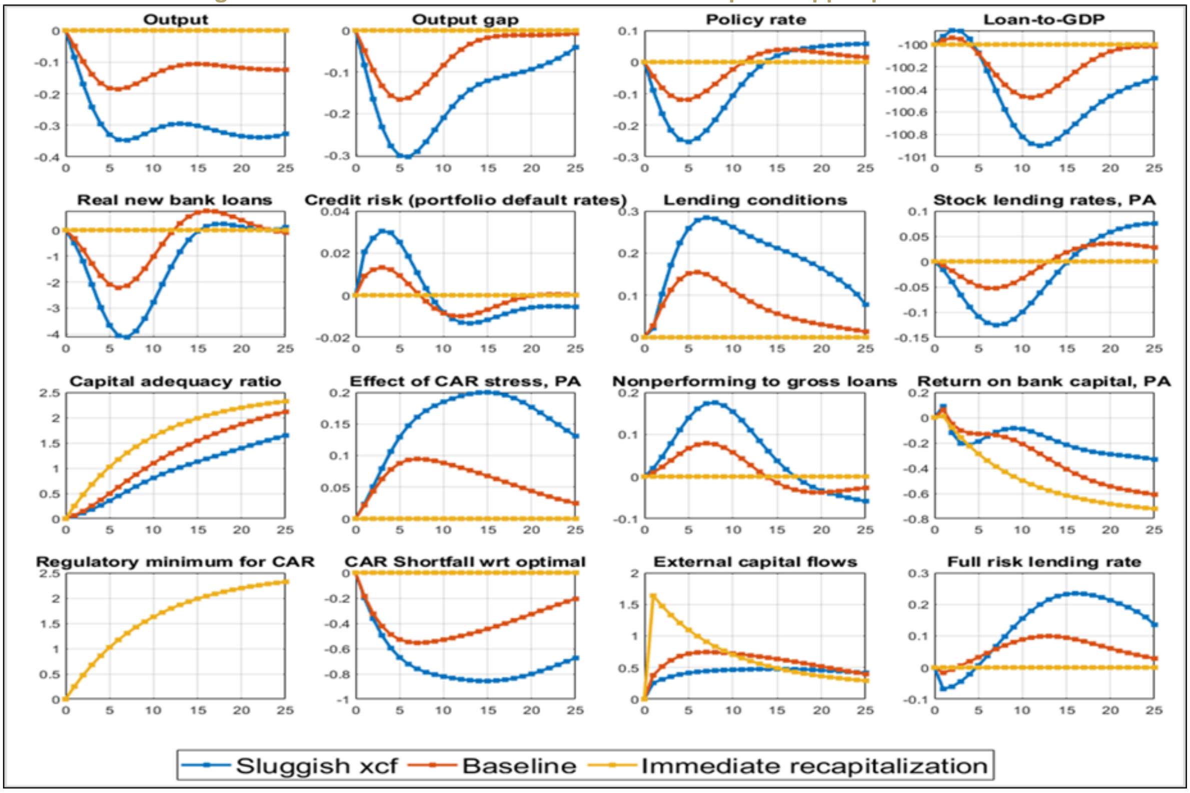


Figure 11: Simulation results for Fast build-up of 2.5pp capital buffer

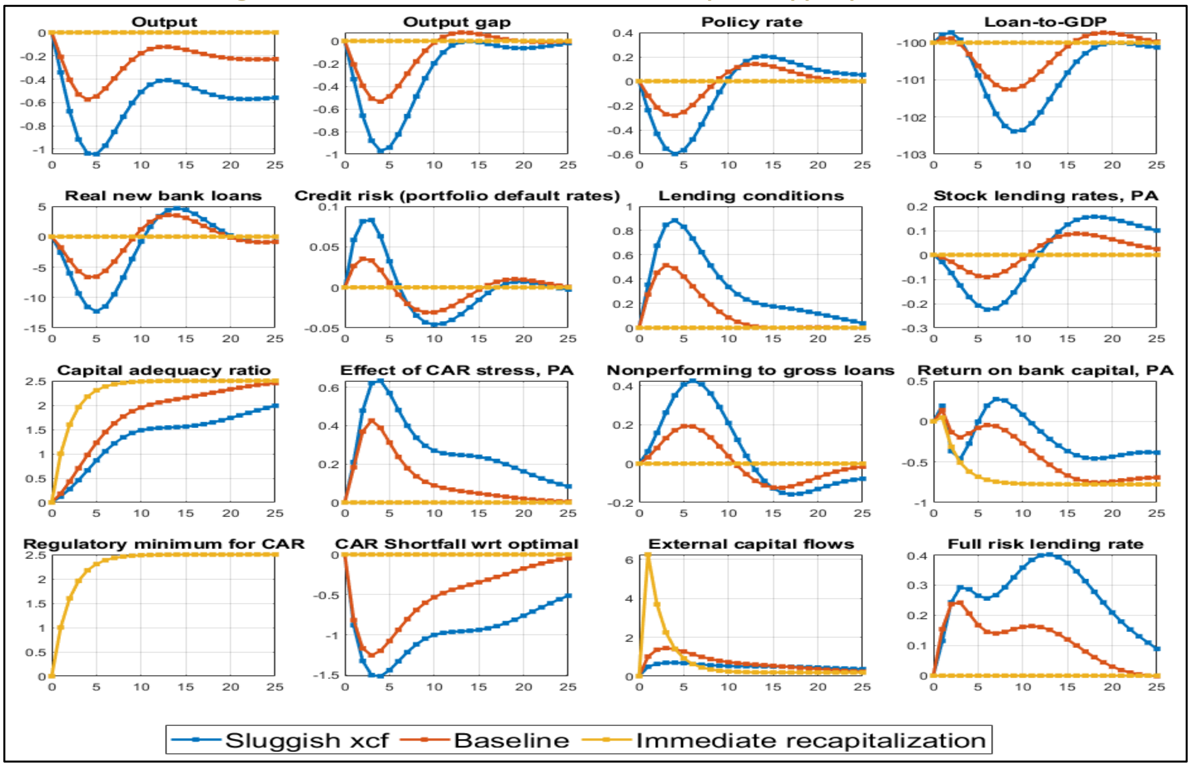
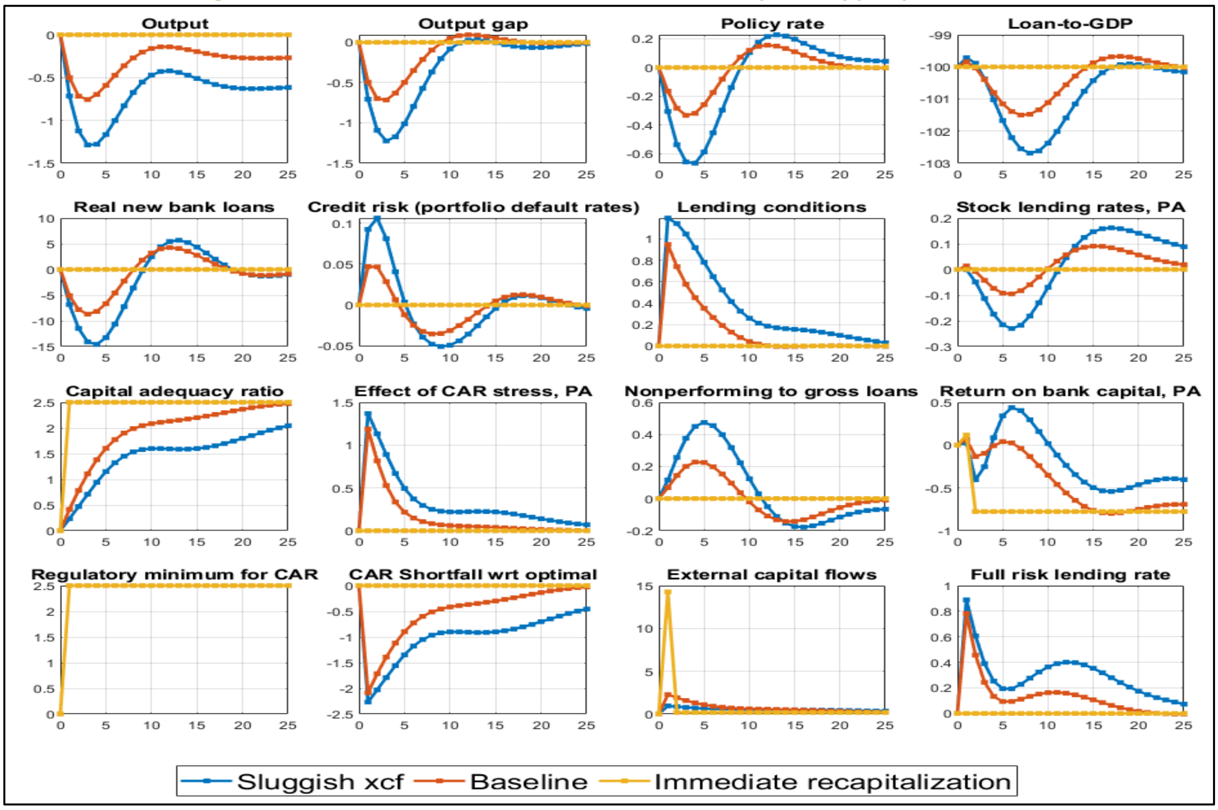


Figure 12: Simulation results for Immediate build-up of 2.5pp capital buffer



For the baseline scenario (c_{xcf}=0.5) and the "sluggish" scenario (c_{xcf}=0.25), the overall dynamic is the same. In fact, the CAR differential leads to a worsening of the lending conditions which discourages the credit creation and leads to a negative output gap pushing the monetary policy to be more accommodative. The policy rate decrease helps improving the lending conditions and gradually close the output gap.

However, the baseline scenario shows better performance in all simulations based on amplitudes compared to the "sluggish" scenario. The higher external capital flows sensitivity to CAR differential reduces the CAR risk surcharge impact on the lending conditions worsening and leads to less output decrease in the baseline.

Consequently, from a policy point of view, and in addition to a gradual CAR build up strategy, more the banks are ready to use their external flows (e.g., dividends) to achieve the regulatory requirement, better is the situation for the economy.

5.3 *Impact of the COVID-19 crisis on the banking sector*

This section examines the impact of the COVID-19 crisis on the banking sector using the DSGE model. A major advantage of the DSGE model is that it allows the effects of the guarantee mechanism to be assessed through a counterfactual analysis. Note however that the results of the analysis depend greatly on the precise form of non-linear functions in the model. As discussed above, these non-linearities are intrinsically hard to calibrate and therefore the quantitative aspects of the simulation should be viewed in that light.

The analysis is conducted under two scenarios:

1. A scenario evaluating the impact of the crisis without government intervention
2. A scenario including the effects of the moratorium and the bank credit guarantee.

Our analysis includes the effects of the moratorium and the guarantee mechanism:

- A direct effect of the moratorium is to prevent a sudden rise in the default rate in the economy following the shock of the COVID-19 crisis. This observation allows us to simulate the effects of the moratorium by temporarily disconnecting the default rate from the macroeconomic conditions during the first half of 2020. During this period, the default rate is exogenously fixed at its level at the beginning of 2020 (1.4% per quarter).

- The objective of the guarantee mechanism is to prevent an increase in lending rates. The effects of this mechanism are simulated by integrating a negative shock on lending rates that allows to maintain lending rates at the level observed during the crisis.

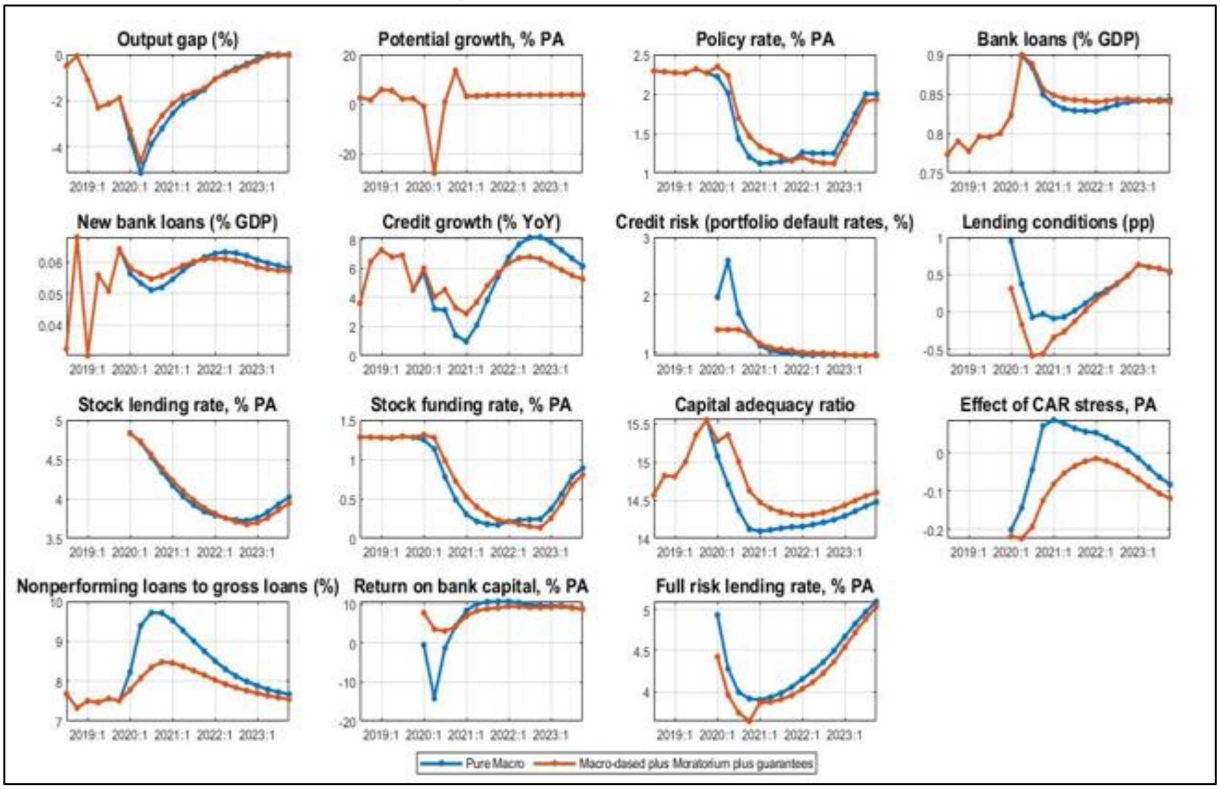
This simulation takes as its starting point the macroeconomic data of the last quarter of 2019. The COVID-19 crisis is simulated in the model as an output gap shock. The size of the output gap shock is calculated from ex-ante observations of the output gap in the years 2020 and 2021.

Figure 13 shows the results of this simulation according to the two scenarios: the first evaluating the impact of the crisis without government intervention in blue and the second with government intervention including the effects of the moratorium and the bank loan guarantee in red.

If the credit stimulus package had not been implemented, the COVID-19 crisis would have led to a decline in the growth of bank credit volume to 1% year-on-year. The volume of NPLs would have risen to 10% of total bank credit volume in 2021, resulting in a significant increase in the default rate to 2.5% per quarter (compared to an average historical level of 1%). Losses in terms of return on capital would have amounted to -15% of the capital stock in 2020. This significant drop in bank returns is explained by both the decline in the rate of credit growth and the increase in delinquencies.

Following the second scenario, which includes the effects of moratorium and credit guarantee, the growth in the volume of bank loans remains around +3%. The volume of NPLs increases to 8.5%, reflecting a modest rise in the default rate on loans to 1.5%. The profitability of the banking sector remains positive and is maintained at a level of +3%.

Figure 13: COVID-19 simulation



Conclusion

DSGE models have become widely used in Central Banks as a policy analysis tool for both monetary and macroprudential policy. In developing countries where banks represent the bulk of the financial system, understanding these linkages at the level of banks' balance sheets is paramount.

Our model for macroprudential policy in Morocco incorporates the main characteristics of the Moroccan banking system and the possible interactions with the real economy. The model includes a representative bank whose balance sheet reflects the asset and liability composition of a typical Moroccan bank, particularly in terms of credit activity, market activity, and nature of assets. The model allows for analysis of the role of real estate assets as a transmission vehicle of shocks. The model integrates macroeconomic shocks to the model, such as inflation and growth. It allows assessing the potential impact of macroprudential instruments that have been enacted in Morocco during the last decade as part of Basel III requirements.

Our model can be used to conduct policy analysis and simulations on issues relating to financial stability and macroprudential policy. The semi-structural nature of the model allows to tackle a wide range of topics. In particular, our simulations highlight the role of external financing, reduction of dividends and progressivity in mitigating the impact of a tightening in capital requirements on the real economy. Our simulations also allow to quantify the positive impact of the guarantee mechanism and moratoriums on the dynamic of loans and the health of the real and financial sector during the COVID-19 pandemic.

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