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A Hybrid model of the banking system

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Abstract

A hybrid model of the banking and the macroeconomic system is used to analyze the impact of capital and minimum reserve requirements on bank profitability. A system dynamics implementation of a macroeconomic model allows superimposing a macroeconomic structure on an agent-based model of the banking system. The former is used to evaluate the impact of business cycles and monetary policy on the banking system. The latter is modelled using an agent-based approach to take heterogeneity and interactions among market participants (agents) into account. The simulation study finds that Return on Equity (ROE) of banks are cyclical, decreasing during a period of negative demand shocks and rebound after the shock has disappeared. In addition, the results illustrate 'political' or 'regulatory cycles': if the macro prudential regulator misjudges the economic cycle and therefore incurs a prediction error, counter-cyclical measures affect the banking system negatively, resulting in significant negative impacts on bank default- and insolvency-frequencies as well as their ROE.

Introduction

From a regulatory perspective, the most important lesson of the global financial crisis 2007 / 2008 is probably that micro prudential banking regulation aimed at preventing the costly failure of individual financial institutions does not suffice to ensure financial stability. The Basel II micro prudential capital requirements had even destabilizing effects by increasing procyclical lending and regulatory arbitrage. As a complement to micro prudential regulation, macro prudential regulation considers general equilibrium effects and interactions with othertypes of public policy that have an impact on systemic financial stability [1]. The Basel III regulatory framework [2] combines micro and macro prudential policies by more stringent and countercyclical capital requirements and the introduction of a leverage ratio, liquidity requirements and a too-big-to-fail surcharge on systematically important financial institutions.

One concern with countercyclical capital requirements is the ability of the macro prudential regulator to 'properly foresee' business cycles: if the macro prudential regulator misjudges the economic environment and wrongly activates the countercyclical capital buffer, for instance, in an economic downturn instead of an upturn, this might lead to 'political cycles' or 'regulatory cycles' jeopardizing the stability of the financial system in general, and the banking system in particular.

Advanced versions of Dynamic Stochastic General Equilibrium (DSGE) models incorporate financial intermediaries [3]. However, these models are based on the assumptions of efficient financial markets and rational expectations and can only explain minor fluctuations around a predetermined state of equilibrium, but not systemic instability with great changes. An encouraging approach to examine systemic financial risk and policies to deal with it are Agent-Based Models (ABM), which use a bottom-up approach of adaptive heterogeneous – potentially learning – agents [4,5]. For instance, ABMs were applied to analyze the influence of either the behavior of financial market investors [6] or banking market structure and regulation [7,8] on systemic risk, or Bookstaber et al., [9] develop an ABM of the wholesale funding market. Neuberger and Rissi [10] apply a full-scale agent-based modelling approach to access financial stability of bank- versus market-based financial systems in general and the Swiss Financial System in particular. One of the major criticisms of agent-based models is their inherent stochastic variability: models with 'too many' stochastic elements will lead to system behavior which is stochastic in nature but does not match the empirical data. In addition, ABMs in general have a lot of degrees of freedom. Therefore, they are difficult to calibrate for practical purposes, in particular, when they include "deep-in-the-model-parameters", i.e. parameters which cannot or only with great difficulty and imprecision be observed / estimated in practice. This argument lies at the heart of a methodological distinction between two general types of agent-based models: a) pure ABM: do not necessarily need to be taken to data to preserve their theoretical relevance as long as micro specifications are plausible. Their application primarily focuses on explaining - through generative techniques - the mechanics of emergent phenomena. Therefore, they are not particularly suited for real-world applications for which some kind of policy guidance is seeked as they are not externally valid able; b) applied ABM: need and have to be descriptively validated and properly calibrated so as to be able to replicate an empirically observed set of data and its major relationships.

This paper aims at implementing a hybrid model – a system dynamics model for the macroeconomic environment and an agent-based model for the banking system – to have "bounded stochasticity", i.e. local randomness where needed and useful within an overall structure which is deterministic in the short-run and changes only gradually in the long-run, for instance, driven by the results of the stochastic model underneath it. The interplay of macro- and microeconomics shall serve as an example: whereas the decisions of the agents can be modeled with stochastic components – and might show short-term rapidly changing behavior – macroeconomic relationships and structures – for instance, GDP contributions of economic sectors – change slowly over time. In such a situation, it might make sense to superimpose onto the short-term stochastic microeconomic behavior some more stable, more slowly changing macroeconomic structure, like, for instance, usage of the direct and indirect intermediation channel. In addition, macroeconomic models depend, in general, on far less parameters than ABMs. The implementation of the hybrid model in this paper tries to accomplish exactly that: combining the bottom-up simulation approach for the banking sector (ABM) with the top-down System Dynamics (SD) approach for the overall economy.

The paper is organized as follows. Section 2 describes the hybrid model. Section 3 explains the parameterization and measurements used. After a presentation of the results in Section 4, Section 5 summarizes and draws conclusions.

The Hybrid Model

Macroeconomic-model (SD)

A system dynamics approach is used to implement the following macroeconomic model of the aggregate demand (AD) and aggregate supply (AS):

1. Demand for goods and services: $Y_t = \overline{Y} - a\left(r_t - \rho\right) + \varepsilon_t$
2. Fisher equation: $r_t = i_t - E_T \prod_{t+1}$
3. Philips curve: $\prod_t = E_{t-1} \prod_t + \varnothing\left(Y_t - \overline{Y}_t\right) + v_t$
4. Adaptive expectations: $E_T \prod_{t+1} = \prod_t$
5. Monetary-policy rule: $i_t = \prod_t + \rho + \theta_{\Pi}\left(\prod_t - \prod_t^*\right) + \theta_Y\left(Y_t - \overline{Y}_t\right)$

with:

endogenous variables:

Y_t Output in period t

Π_t Inflation in period t

r_t Real interest rate in period t

i_t Nominal interest rate in period t

$E_t \Pi_{t+1}$ Expected inflation for period t+1, with expectations taken at point in time t

exogenous variables:

$\overline{Y}_t$ Natural level of output in period t

Π_t^* Central bank's target inflation for period t

$\in_t$ Demand shock in period t

v_t Supply shock in period t

predefined variable:

$\prod_{t-1}$ Previous period's inflation

and parameters:

α Responsiveness of the demand for goods and services to the real interest rate

ρ Natural rate of interest

ϕ Responsiveness of inflation to output in the Philips curve

θ_{Π} Responsiveness of the nominal interest rate to inflation in the monetary-policy rule

θ_Y Responsiveness of the nominal interest rate to output in the monetary-policy rule

The monetary-policy rule (eqn. (5)) is inspired by the Taylor-Rule. The long-run equilibrium of the above model is given, when $\varepsilon_t = v_t = 0$ (i.e. when there are no shocks) and $\prod_t = \prod_{t-1}$ (i.e. when inflation has stabilized). Applying this to the above model equations leads the long-run equilibrium values of the endogenous variables:

$$r_t = \rho\,;\, r_t = \rho\,;\, \pi_t = \pi_t^*\,;\, E_t\pi_{t+1} = \pi_t^*\,;\, i_t = \rho + \pi_t^*$$

Applying the quantity theory of money

*M*V=P*Y*

with:

M Money

V Income velocity of money

P Price level

Y Output

One can also work with money (M) instead of interest rates. For simplicity, it is assumed that the income velocity of money (V) is constant and equal to 1. One therefore interprets the quantity of money equation as representing aggregate demand (Cambridge equation).

Instead of working with adaptive expectations, one could also implement the macroeconomic model with rational expectations: decisions regarding investments, production and the future supply of goods and services depend on the expectations of market participants w.r.t. future economic developments. Therefore, market participants aim at gathering and incorporating all available relevant information and use it rationally / optimally in their decision-making process. Agents of the economic system try to minimize systematic errors in their forecasts / predictions (in the above case w.r.t. the price level, in particular). The theory of rational expectations obviates such systematic errors: market participants suffer losses due to wrong decisions based on forecast errors. Therefore, they minimize the forecast error of the price level:

$$min.E\left[P_t - E\left(P_t \middle| \Omega_t\left(z\right)\right)\right]^2$$

where:

$\grave{U}_t(z)$ Information set at time t w.r.t. the market z

Monetary as well as real innovations (changes in the preference structure of market participants, technological changes) can change the demand for goods and the nominal price level. Agents face a signal extraction problem: unexpected price increases due to a demand push need to be traced back to / interpreted as either entirely originating from nominal or real causes or a combination of the two. How market participants interpret an unexpected change in the price level, $P_t - E\left(P_t \middle| \grave{U}_t(z)\right) \neq 0$, depends on their assessment / judgment of the relevance of monetary and real innovations responsible for the unexpected change. The impact of monetary innovations on the real supply of goods and services, y_t is therefore a function of the forecast error weighted with the relative importance of monetary and real innovations, ψ, and the elasticity of supply (reaction coefficient), γ:

$$y_t = \Psi\gamma\left(P_t - E\left(P_t \middle| \Omega_t\left(z\right)\right)\right)$$

with:

$$0 \le \psi \le 1$$

Dominance of monetary innovations will lead to: $\psi \to 0$, whereas dominance of real innovations results in $\psi \to 1$.

An Agent-Based Model for the Banking System (ABM): the microeconomic model

Interpreting the financial system as complex, social, adaptive and interacting system [11], and an agent-based model is applied to the banking system to provide for emergent phenomena resulting from interactions of micro-rules executed by heterogeneous agents. The agent-based model part of the hybrid model is mainly the ABBA model of Chan-Lau [12] with some minor modifications in order to fit together with the macroeconomic model as described above. The major features of the AB model are summarized as follows:

The model considers three types of agents in the banking system: savers, borrowers, and banks, and one type of interbank linkages, interbank loans. The banking system is geographically divided into different regions, across which, both the savers and borrowers are homogenously distributed. In the outset of the simulation, each region is dominated by a regional bank, which raises deposits from savers and makes loans to corporations. In subsequent periods, banks may start raising deposits and extending loans in different regions:

Savers: savers are geographically homogeneously distributed but heterogeneous w.r.t. the probability of withdrawing deposits and shifting to another bank. This feature ensures that the ABM is able to model deposit in- and outflows and the corresponding repercussions for the liquidity position of the involved banks (as well as the overall banking system via the interbank loan market). Savers with deposits at solvent banks receive interest payments: the deposit rate is set equal to the (nominal) risk-free rate, assuming the deposits are risk-free. The interest incomes consumed and not reinvested in the bank account. As there is no deposit insurance in this model, savers remain solvent as long as their bank does not default. In case of a bank default, its loan portfolio is liquidated at a loss owing to haircuts (fire-sale losses). The total assets after this liquidation procedure (proceeds from the liquidated loan portfolio and the available reserves) are used to reimburse the depositors. In case of insufficient proceeds savers get paid on a first-come, first-served basis: savers who are not paid become insolvent.

Borrowers: The borrowers (modelled as individual loans) are geographically homogeneously distributed, also homogeneous regarding the loan amount (1 unit) but heterogenous w.r.t: the probability of default, the associated risk-weight, recovery rate, loan rate, and the hair-cut of the fire-sale loss. Based on the probability of default and loss given default, the bank quotes a loan rate based on the following simple pricing rule:

$$r_t^{l,i} = \mu_t^i \left[\frac{\left(1 + r_t^{free} - p_t^{l,i} \times rr_t^{l,i}\right)}{1 - p_t^{l,i}} - 1 \right]$$

with: $r_t^{l,i}$ = loan rate for loan l at bank i in period t, μ_t^i = bank i's markup, $r_t^f ree$ = the (nominal) risk-free interest rate in period t, $p_t^{l,i}$ = default probability of loan l at bank i, $rr_t^{l,i}$ = recovery rate of loan l granted by bank i in period t.

Loans are granted under the calculated conditions as long as the bank remains compliant with capital and reserve requirements after adding the loan to the current loan portfolio. At the end of a period, all non-defaulted loans spay interest based on the agreed loan rate, and the loan is rolled over for another period. If the loan defaults, the bank receives the recovery amount of the corresponding loan.

Banks: Banks in the ABBA model are pure depository institutions: they raise deposits to fund risky loans, after complying with minimum reserves requirements. For the risky loans granted, banks provision against the expected losses in the loan book. In addition, banks are subject to minimum regulatory capital requirements:

Minimum capital requirement: $E_t^i \geq \left(\sum_{t \varepsilon B_t^i} L_t^{l,i} \times rw_t^{l,i}\right) \times CAR$

Minimum reserves requirement: $Res_t^i \geq \left(\sum_{d \varepsilon D_t^i} d_t^i\right) \times MRR$

Loan loss provisions (for expected losses): $prov_t^i = \sum_{l \varepsilon B_t^i} p_t^l \times L_t^{l,i} \times \left(1 - rr_t^{l,i}\right)$

with: E_t^i = equity capital of the bank i at time t, B_t^i = loan portfolio of bank i at time t, $rw_t^{l,i}$ = loan amount of loan l at bank i at time t, $rw_t^{l,i}$ = risk weight of the loan, CAR = regulatory capital adequacy ratio, Res_t^i = reserves held at bank i in period t, $\sum_{d \varepsilon D_t^i} d_t^i$ = total deposits at bank i at time t, MRR = minimum reserve ratio, $prov_t^i$ = loan loss allowances of bank i in period t, rr_t^l = default probability of loan l, $rr_t^{l,i}$ = recovery rate of loan l granted by bank i in period t.

Solvent but undercapitalized banks could deleverage or conduct risk-weight optimization to increase its reserves and boost its capital to risk weighted assets. There exists an interbank loan market for unsecured interbank loans: banks with excess reserves lend to other banks to meet the reserve requirement. In each period, the sequence of events in the banking system is as follows:

The solvency of every bank is evaluated, after considering actual defaults in the loan book:

$$NII_t^i = \sum_{t \in B_t^i} L_t^{l,i} \times r_t^{l,i} + Res_{t-1}^i \times r_t^R - \sum_{d \in D_{t-1}^i} d_{t-1}^i \times r_t^{d,i}$$

with: NII_t^i = net interest income of bank i in period t, r_t^R = interest earned on reserves, $r_t^{d,i}$ = deposit rate paid to savers.

Defaulting loans, $\in B_t^{D,i}$, lead to credit losses, $CLoss_t^i$:

$$CLoss_t^i = \sum_{\in B_t^{D,i}} L_t^{l,i} \times \left(1 - rr_t^{l,i}\right),$$

a corresponding change in the level of loan loss provisions, $\Delta prov_t^i$:

$$\Delta prov_t^i = \sum_{l \in B_t^{S,i}} p_t^l \times L_t^{l,i} \times \left(1 - rr_t^{l,i}\right) - \sum_{l \in B_t^{S,i} \square B_t^{D,i}} p_t^l \times L_t^{l,i} \times \left(1 - rr_t^{l,i}\right)$$

with: RWA_t^i = solvent loans

and to a decline of the risk-weighted assets, RWA_t^i, to:

$$RWA_t^i = \sum_{\in B_t^{S,i} UB} {}^{D,i} rw_t^{l,i} \times L_t^{l,i} - \sum_{l \in B_t^{D,i}} rw_t^{l,i} \times L_t^{l,i}$$

The new equity – after credit losses – equals:

$$E_t^i = E_{t-1}^i + NII_t^i - Closs_t^i - \Delta prov_t^i,$$

and the reserves are:

$$Res_t^i = Res_{t-1}^i + NII_t^i + \sum_{l \varepsilon B_t} {}^{D,i} rr_t^{l,i} \times L_t^{l,i} - \Delta prov_t^i$$

If $E_t^i \leq 0$, the bank is insolvent is the loan book is liquidated at fire-sale values, generating the following proceeds:

$$FS_t^i = \sum_{l \in B_t^{S,i}} L_t^{l,i} \times \left(1 - fs_t^{l,i}\right)$$

with: $fs_t^{l,i}$ = fire-sale loss.

The losses from second-round effects affecting interbank exposures, credit losses in the interbank market, $IBLoss_t^i$, is calculated:

$$IBLoss_t^i = \sum_{b \in FI_t^{D,i}} IB_t^{i,b}$$

with: $FI_t^{D,i}$ = set of defaulted banks with liabilities to bank i, $IB_t^{i,b}$ = interbank loan amount bank i lent to bank b.

The equity of the bank after these second-round effects, $E_t^{IB,i}$, is:

$$E_t^{IB,i} = E_t^i + \sum_{b \in FI_t^{S,j}} IB_t^{i,b} \times r_t^{IB,i,b} - \sum_{b \in FI_t^{-i}} IB_t^{b,i} \times r_t^{IB,b,i} - IBLoss_t^i$$

with: $r_t^{IB,i,b}$ = interbank rates charged by bank i, FI_t^{-i} = interbank rates charged to bank i, FI_t^{-i} = set of all banks excluding bank i.

The reserves of bank i after the second-round effects, $Res_t^{IB,i}$, is:

$$Res_t^i + \sum_{b \in FI_t^{S,j}} IB_t^{i,b} \times \left(1 + r_t^{IB,i,b}\right) - \sum_{b \in FI_t^{-i}} IB_t^{b,i} \times \left(1 + r_t^{IB,b,i}\right) - IBLoss_t^i$$

These second-round effects may result in bank failures generating another sequence of second-round effects.

The banks optimize the loan portfolio composition to meet capital requirements if needed. After the second-round effects, a bank may remain solvent but undercapitalized, i.e. $0 \le E_t^i \le RWA_t^i \times CAR$. The bank tries to improve its balance sheet positions by performing risk-weight optimization (deleveraging). While the main effect will be the release of provisions and an increase of equity resulting in an offset of loan liquidation losses and a reduction of the risk-weighted assets, a side effect is that the deleveraging could potentially increase the reserve ratio as long as the released provisions exceed the losses stemming from the liquidation of the loans. The result of the optimization procedure is that the bank retains a subset of the loans, of its $B_t^{(RWO,S,i)}$, solvent loan portfolio, $B_t^{(S,i)}$, satisfying:

$$B_t^{RWO,S,i} \subset B_t^{S,i} s.t.\ CAR\left(RWA\left(B_t^{RWO,S,i}\right)\right) \ge CAR \ge CAR\left(RWA\left(BB_t^{S,i}\right)\right)$$

Banks need to decide whether to pay dividends or not, expand their loan portfolio, and access the interbank market if needed to cope with idiosyncratic liquidity shocks. Banks set a maximum capital ratio target and after determining the amount of equity need to meet this target, they return the excess equity, xE_t^i, to its shareholders as dividends. As these dividends are paid from the bank's reserves, the dividend payment is also constraint by the minimum reserve requirement (regulatory + internal add-on = internal minimum reserve target). Therefore:

$$xE_t^i = E_t^i - E_t^{target}$$

with: $E_t^{target} = \alpha \times CAR \times RWA_t^i$, where $xRes_t^i$ determines the bank's desired (internal) capital ratio, and excess reserves, $xRes_t^i$,:

$$xRes_t^i = Res_t^i - Res_t^{target}$$

with: $\mathrm{Re}s_t^{target} = \beta \times MRR \times D_t^i$.

The dividend payment of bank i in period t, div_t^i, is therefore:

$$div_t^i = \min\left\{xE_t^i, xRes_t^i\right\}.$$

From a macroeconomic point of view, it is assumed that Fama's theory [13] of financial intermediation and the Real-Bills Doctrine hold true: the balance sheet positions of banks (assets) represent optimal portfolios of real investment projects. As the banks' portfolio selection focuses on the actual, real profitability, their portfolios passively follow the real economic development. Financial crises are therefore the result of negative, real innovations (reverse causation). The real economic development is modelled via an SD-approach of the above equations. The real sector will be exposed to shocks (negative demand shocks) and the financial system adjusts to cater for the demand of money to pay for goods and services (law of reflux).

Parametrization of the models and measurements

In this section, the parameterization and measurements of the SD and AB model are described.

Parameterization

Macroeconomic model

The parametrization of the macroeconomic model as described in section 2 is as follows (Table 1):

In addition, the following assumptions are made Term-structure of interest rates is flat. Therefore, it can be assumed that the fed-funds rate and the (nominal) risk-free rate (as proxied by the 1-year Treasury rate) are identical.

The interest paid on excess reserves (IOER rate) is the same as the interest paid on mandatory reserves (IERR rate).

The interest paid on excess reserves is equal to the (nominal) risk-free rate.

There are no bid-ask-spreads for interest rates.

The effective fed-funds rate equals the target fed-funds rate.

The Libor rate equals the fed-funds rate.

ABM

Savers:

9,000 savers homogenously distributed across 10 geographical regions.

Savers hold bank deposits with time-varying, nominal balance to accommodate for the change in money demand and supply.

Table 1: Parametrization of the macroeconomic model.

Endogenous variables	(Initial) Value
Y_0	100
π_0	2%
r_0	2%
i_0	4%
$E_0\pi_1$	2%
Exogenous variables:	
$\overline{Y}_0 = \overline{Y}_t$	100 = constant
$\pi_0^* = \pi_t^*$	2% = constant
$\in_\tau$	$\in_\tau = 0$ for $t \in [0,..., 9,15,...,45]$, for all simulation runs $\in_\tau = -10$ for $t \in [10,...14]$, for all simulations with negative demand shock
$\upsilon_0 = \upsilon_t$	0 for all t and for all simulation runs
Predefined variable:	
π_{-1}	2%
Parameters:	
α	1.0
ρ	2.0
ϕ	0.25
θ_π	0.5
θ_Y	0.5

The deposit rate paid by banks is time-varying and equals the risk-free interest rate. Interest on deposits is consumed by the savers, i.e. do not accrue in their savings account.

A saver withdraws deposits and changes banks with a probability sampled from a discrete uniform distribution $\mathcal{U}(0,10)$, i.e. 0 – 10%.

Borrowers / Loans

The number of available loans: 20,000, evenly distributed across the 10 geographical regions.

Loan amount: time-varying, nominal balances to accommodate for the change in money demand and supply.

Recovery rate: 40%

Heterogenous probability of default sampled from a discrete uniform distribution U(0,2), i.e. a probability between 0% and 2%.

The risk weight of a loan is a linear function of its probability of default, given by 0.5 + 5 × PD.

Fire-sale loss: $\mathcal{U}(0,10)$, i.e. values between 0 and 10% of the face value of the loan.

Loan rate quoted by a bank: $r_t^{l,i}$, as explained in section 2. Mark-up, μ_t^i: 1.2.

Banks:

Initial number of banks: 10.

Initial equity of each bank: 100.

Bank's (internal) reserve ratio: 1.5 × minimum reserves ratio

Maximum capital ratio preferred by the bank: 1.5 × CAR. Dividends are paid (out of reserves) if the capital exceeds the maximum capital ratio.

Interbank loans:

Interbank loan rate: Libor rate.

Banks with excess reserves lend to well capitalized but illiquid banks.

Regulatory requirements:

Minimum capital requirements as measured by equity / RWA vary according to the corresponding simulation runs and take values in the set of [4%,8%,12%,16%].

Minimum reserve ratio: varies according to the corresponding simulation runs and take values in the set of [3%,4.5%,6%].

Central Bank

The central bank implements a monetary policy according to the Taylor rule described in section 2.

In addition, the central bank acts as macroprudential regulator in the respective runs, adjusting the minimum capital / or reserve requirements according to the perceived macroeconomic environment (for further details, see results section).

Measurements

The main purpose of the analyses is to investigate the impact of a demand shock on profitability of the banking system under different regulatory regimes. Therefore, the following measurements are calculated for every period tin all runs:

return on equity for bank i in period t: $ROE_t^i = \frac{dividends_t^i}{Equity_{t-1}^i}$

the proportion of defaulting banks in period t, the default frequency,

$$DF_t = \frac{number\ of\ defaulting\ banks_t}{number\ of\ solvent\ banks_t}$$

The proportion of insolvent banks in period t, the insolvency frequency,

Table 2: Simulation configurations.

Simulation No.	Description	(Changed) Parameter Settings
1-12 (results in section 4.1)	No economic cycles, base-case scenarios for all combinations of minimum capital requirements $\in[4\%,8\%,12\%,16\%]$ and minimum reserve ratio $\in[3\%,4.5\%,6\%]$	Number of MC-simulations: 100; number of periods: 46; $\epsilon_\tau = 0$ for $t \in [0,...45]$
13-24 (results in section 4.2)	Economic cycle: negative demand shock in periods 10-14, regulator does not adjust the originally set minimum capital and reserve requirements, all combinations of minimum capital requirements $\in[4\%,8\%,12\%,16\%]$ and minimum reserve ratio $\in[3\%,4.5\%,6\%]$	Number of MC-simulations: 100; number of periods: $\epsilon_\tau = -10$ for $t \in [10,...14]$ $\epsilon_\tau = -10$ for $t \in [10,...14]$
25-36 (results in section 4.3)	Economic cycle: negative demand shock in periods 10-14, regulator adjusts the originally set minimum capital requirements to 50% in periods 9-14, all combinations of minimum capital requirements and minimum reserve ratio $\in[3\%,4.5\%,6\%]$	Number of MC-simulations: 100; number of periods: 46; $\epsilon_\tau = 0$ for $t \in [0,...9,15,...,45]$ $\epsilon_\tau = 0$ for $t \in [0,...9,15,...,45]$ $\epsilon_\tau = -10$ for $t \in [10,...14]$
37-48 (results in section 4.4)	Economic cycle: negative demand shock in periods 10-14, regulator adjusts the originally set minimum capital requirements to 150% in periods 9-14, all combinations of minimum capital requirements $\in[4\%,8\%,12\%,16\%]$ and minimum reserve ratio $\in[3\%,4.5\%,6\%$	Number of MC-simulations: 100; number of periods: 46; $\epsilon_\tau = 0$ for $t \in [0,...9,15,...,45]$ $\epsilon_\tau = -10$ for $t \in [10,...14]$
49-60 (results in section 4.5)	Economic cycle: negative demand shock in periods 10-14, regulator adjusts the originally set minimum reserve requirements to 150% in periods 5-9 (lead time), then reverts to the original configuration, all combinations of minimum capital requirements $\in[4\%,8\%,12\%,16\%]$ and minimum reserve ratio $\in[3\%,4.5\%,6\%]$	Number of MC-simulations: 100; number of periods: 46; $\epsilon_\tau = -10$ for $t \in [10,...14]$ $\epsilon_\tau = -10$ for $t \in [10,...14]$
61-72 (results in section 4.6)	Economic cycle: negative demand shock in periods 10-14, regulator adjusts the originally set minimum reserve requirements to 50% in periods 5-9 (lead time), then reverts to the original configuration, all combinations of minimum capital requirements $\in[4\%,8\%,12\%,16\%]$ and minimum reserve ratio $\dot{o}_t = -10\, fort \in [10,\ldots,14]$	Number of MC-simulations: 100; number of periods: 46; $\epsilon_\tau = -10$ for $t \in [10,...14]$ $\epsilon_\tau = -10$ for $t \in [10,...14]$

$$IF_t = \frac{number\ of\ insolvent\ banks_t}{number\ of\ solvent\ banks_t}.$$

The above measures are then averaged over all banks in each period t. Additionally, the corresponding averages over the whole time period simulated as well as the subperiod containing the demand shock are calculated.

Simulations

The following simulation configurations were run (Monte-Carlo simulations) (Table 2).

Results

All results reported start from period 5: period 0 to 4 are used as 'burn-in'-period.

No Economic Cycles

For simulation no. 1-12, the results for ROE are depicted in below Figures 1 to 3:

Table 3 summarizes the average means of ROE of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Main findings

In general, for higher minimum capital requirements – given any minimum reserve requirement – the ROE declines (F1).

Whereas this relationship holds true for all periods (except for a slight reversal of this relationship for the case with 3% minimum reserve requirements), ROEs converge up to period 40, after which they start diverging (F2).

ROEs decline more or less steadily over time as defaults on the loan book kick in with the path for the regulatory regime involving minimum reserve requirements of 3% showing the highest volatility (F3).

Given a minimum capital requirement, higher minimum reserve requirements lead to higher ROEs. This is due to a particular feature / assumption of the model: reserves are invested at the risk-free interest

Table 3: Mean ROEs for simulation no. 1-12.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	9.8%	6.2%	5.8%	5.0%
	4.5%	9.4%	7.6%	6.3%	5.3%
	6%	11.6%	8.0%	6.5%	5.4%

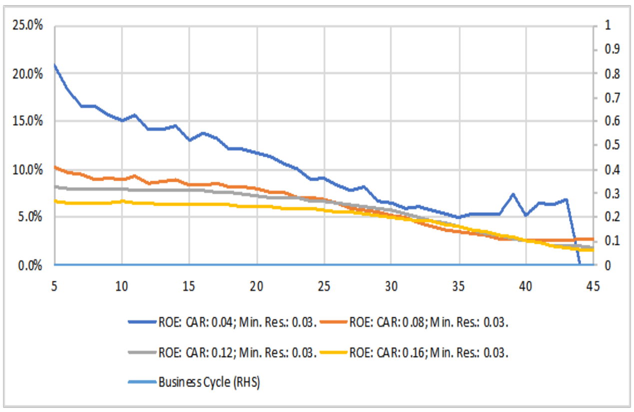

Figure 1: Evolution of ROE over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

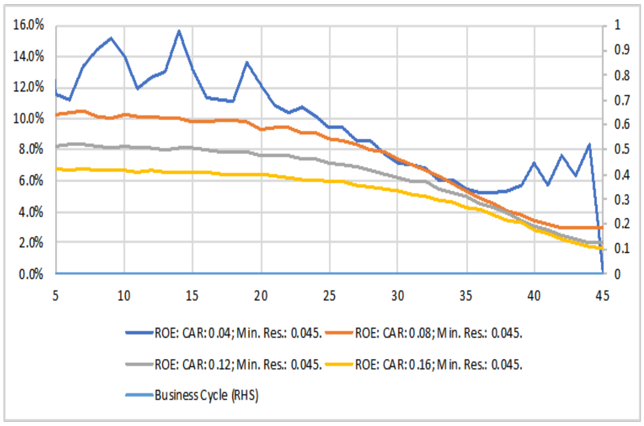

Figure 2: Evolution of ROE over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

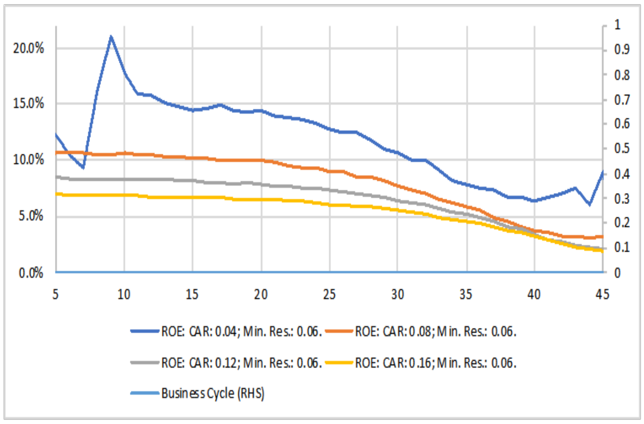

Figure 3: Evolution of ROE over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

rate and lead to a superior return profile compared to an investment in loans. Although the latter generates higher expected returns due to the incorporation of expected credit losses in the loan rate, the results show that the compensatory effect of the losses from the investment in loans on the higher expected return result in lower ROEs compared to a default-free investment of the reserves (F4).

Table 4 summarizes the average means of the default- and insolvency-frequencies (in brackets) of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

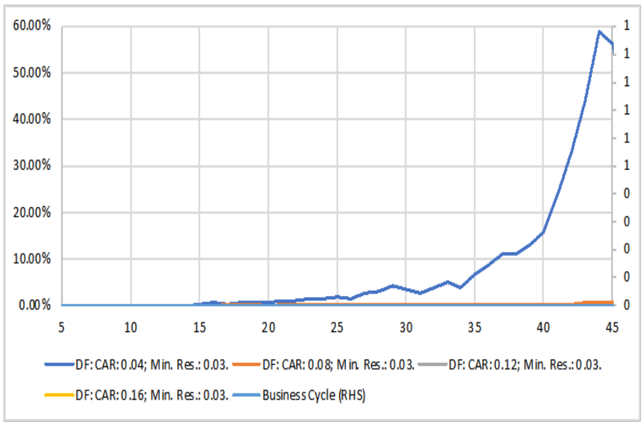

Figure 4: Evolution of DF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

Table 4: Mean DFs and IFs for simulation no. 1-12.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	7.8% (34.4%)	0.2% (16.6%)	0.0% (3.8%)	0.0% (1.5%)
	4.5%	4.7% (13.8%)	0.0% (0.3%)	0.0% (0.0%)	0.0% (0.0%)
	6%	2.2% (1.2%)	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)

Main findings

In general, for higher minimum capital requirements – given any minimum reserve requirement – the DF and IF decline (F5).

The same is true for increasing minimum reserve requirements – given a minimum capital requirement (F6).

For low minimum capital requirements (CAR = 4%) the probability of default increases (statistically) significantly over time for any configuration of minimum reserve requirements (F7).

Looking at the above table of the average means of the default- and insolvency-frequencies, one could conclude that minimum capital and liquidity requirements are substitute regulatory measures for managing DFs and IFs, but they come at different costs (as measured by a change in the average ROE) as is obvious by comparing the different regulatory configurations in table 3 of the average ROEs (F8).

Economic Cycles: Passive Macroprudential Regulator.

In this section, the results for an economy going through an economic cycle represented by a (real) no-growth-period for time 5-9, a (real) negative demand shock in periods 10-14, and a (real) no-growth-period for time 15-45. It is assumed that the regulator is passive, i.e. does not adjust the originally set minimum capital and reserve requirements.

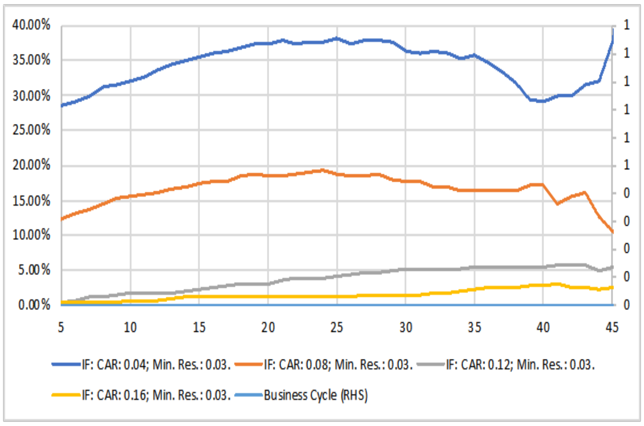

Figure 5: Evolution of IF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

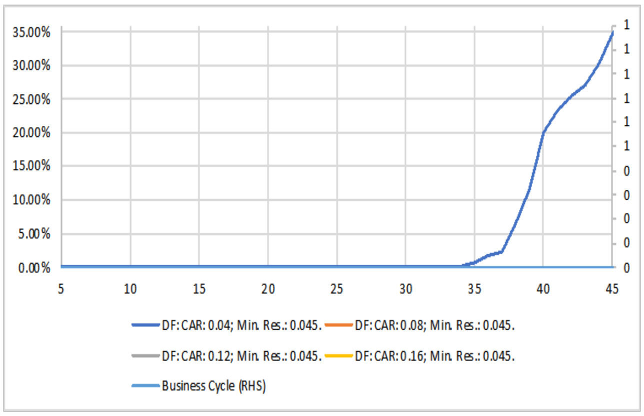

Figure 6: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

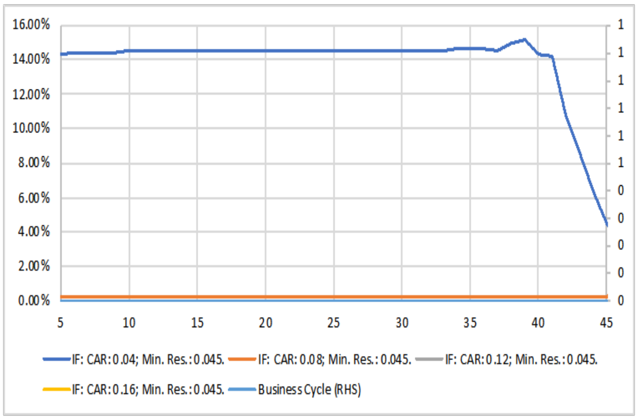

Figure 7: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

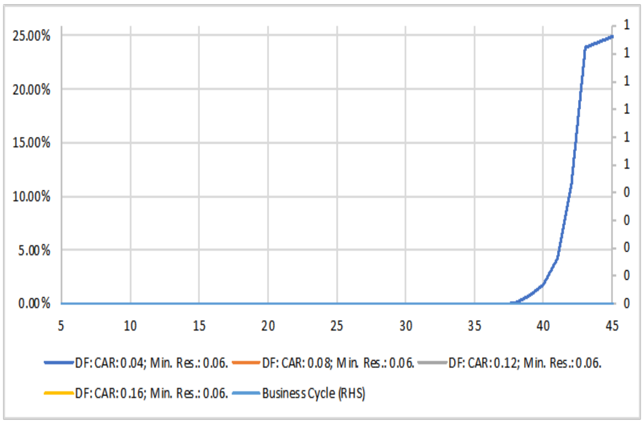

Figure 8: Evolution of DF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

Table 5: Mean ROEs for simulation no. 13-24.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	9.7%	5.9%	6.1%	5.1%
	4.5%	9.4%	7.6%	6.4%	5.4%
	6%	9.5%	7.9%	6.5%	5.5%

Table 5 summarizes the average means of ROE of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Main findings:

In general, finding (F1) of section 4.1 still holds true (F9).

As in finding (F2) of section 4.1, one observes a general convergence of the ROEs as time passes, but there are two points in time where convergence happens: one in period 15 (the end of the negative demand shock) and one in period 40: after the end of the negative demand shock ROEs first diverge to converge thereafter again (F10).

Finding (F3) of section 4.1 still persists with the general downward trend being disrupted during the period of the negative demand shock: during that time, ROEs are below the trend decrease, rebounding above it after the end of the negative demand shock: overreaction-/ overcompensation-effect of the system. This behavior is more pronounced – for a given minimum reserve ratio – the lower the CAR. (F11).

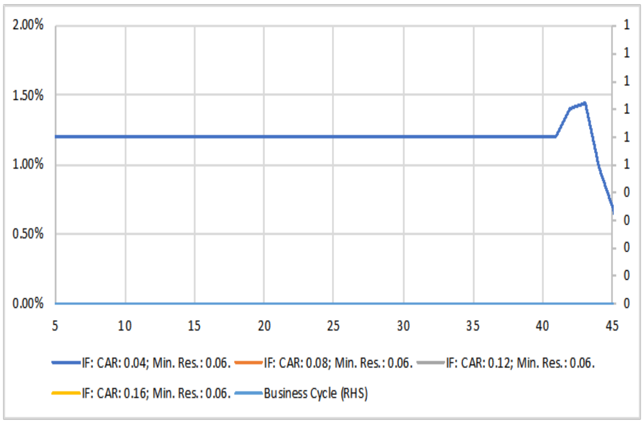

Figure 9: Evolution of IF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

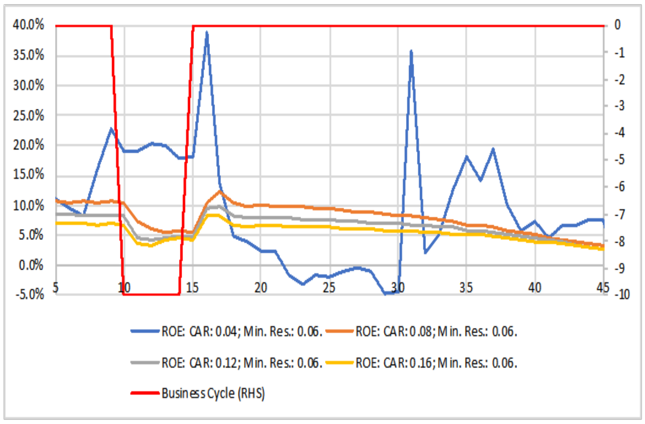

Figure 12: Evolution of ROE over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

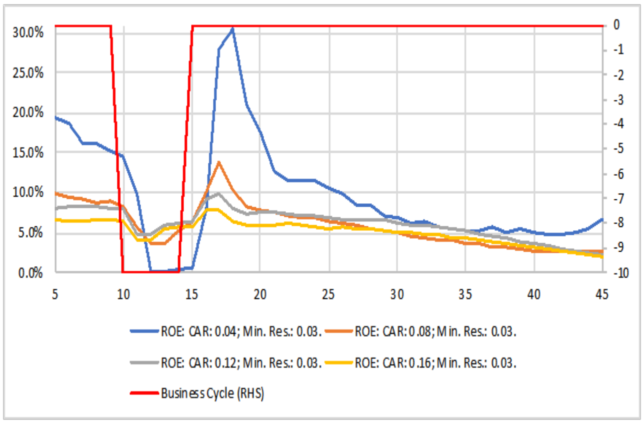

Figure 10: Evolution of ROE over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

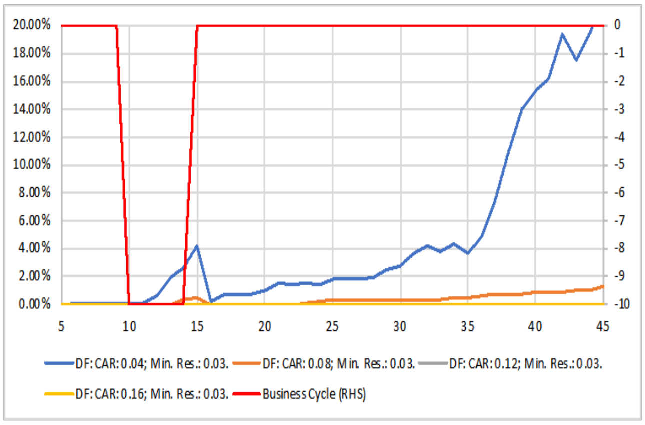

Figure 13: Evolution of DF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

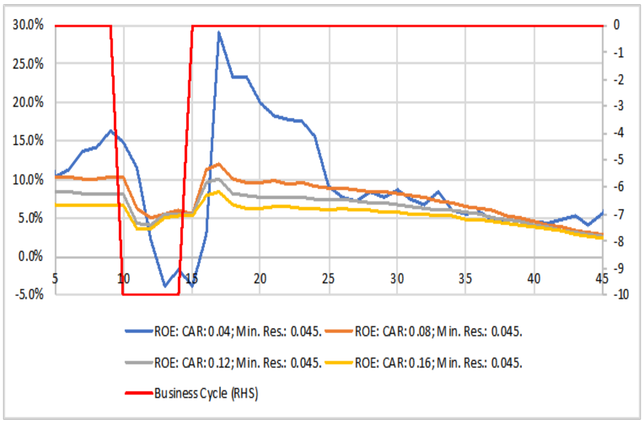

Figure 11: Evolution of ROE over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

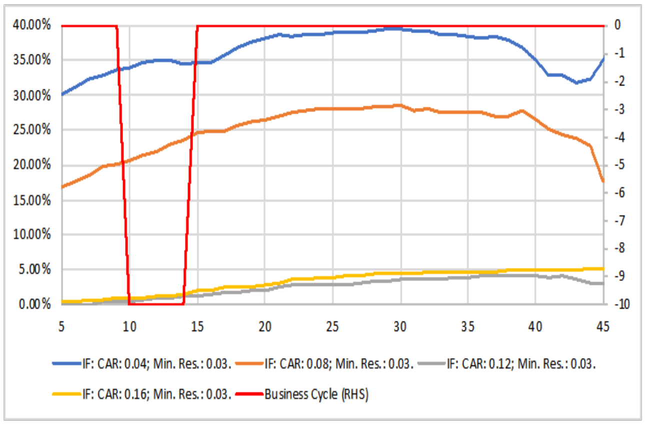

Figure 14: Evolution of IF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

Finding (F4) of section 4.1 is also confirmed (F12).

Whereas the differences in the average means of ROE of all banks over the whole time period considered (Table 3 and Table 5) are statistically insignificant (F13), the ROEs during the negative demand shock are – for any regulatory configuration – statistically significantly different – lower – compared to the corresponding ROEs without an economic cycle (F14).

Low capital requirements (CAR = 4%) – for any configuration of the tested minimum reserve requirements – are associated with statistically significantly higher intertemporal ROE-volatility when compared to regulatory regimes with correspondingly higher CARs (F15).

Table 6 summarizes the average means of the default- and insolvency-frequencies (in brackets) of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Main findings:

In general, findings (F5) and (F7) of section 4.1 still holds true (F16).

Comparing the DFs and IFs for the corresponding run configuration

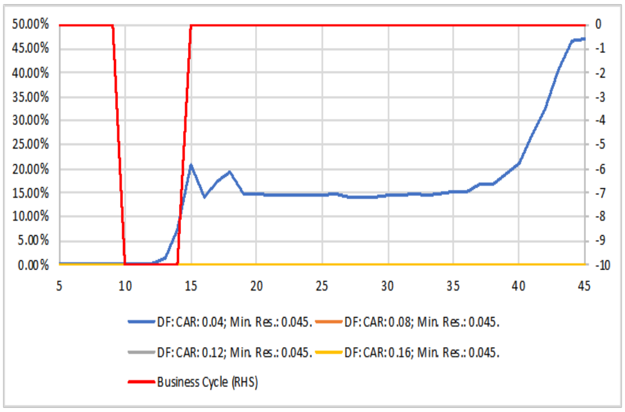

Figure 15: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

Table 6: Mean DFs and IFs for simulation no. 13-24.

		Minimum capital requirement:			
Minimum reserve requirement		4%	8%	12%	16%
	3%	4.8%* (36.3%*)	0.3%* (25.0%*)	0.0% (2.5%*)	0.0% (3.3%*)
	4.5%	14.9%* (19.6%*)	0.0% (0.3%)	0.0% (0.0%)	0.0% (0.0%)
	6%	28.6%* (3.9%*)	0.1%* (0.0%)	0.0% (0.0%)	0.0% (0.0%)

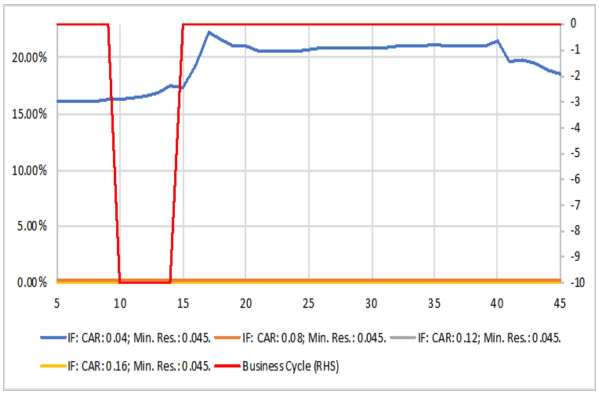

Figure 16: Evolution of IF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

with and without an economic cycle, one not only gets statistically significant differences across all the time periods as indicated by (*) in table 6, but also, the DFs and IFs during the demand shock periods (10-14) differ statistically significantly at the 95% level (two-sided) from their counterparts in the runs with no economic cycle (F17).

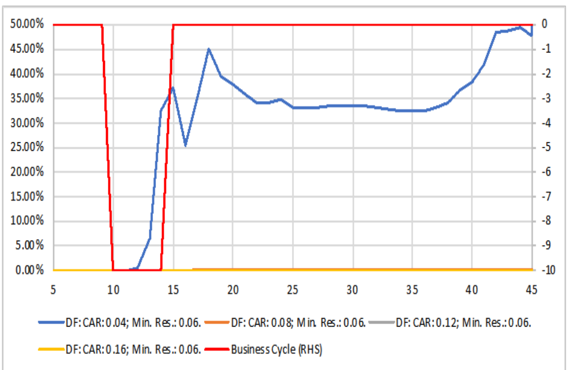

Figure 17: Evolution of DF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

Conclusion

The statistically significant, procyclical behavior of the ROEs, DFs and IFs might suggest that countercyclical behavior of the macroprudential regulator could try to mitigate these effects by pro-actively changing the regulatory regime in anticipation of the negative demand shock. Potential repercussions on ROE, DF and IF of getting the timing, direction and / or size of the demand shock wrong, i.e. the potential manifestations of 'regulatory' or 'policy' cycles, are investigated further in the following sections.

Economic Cycles: Active Macroprudential Regulator: Correct Foresight One Period Ahead.

In this section, the results for an economy going through the same economic cycle as described in section 4.2 are presented. It is assumed that the regulator actively adjusts the originally set minimum capital requirements to 50% of their respective values during the demand shock period, starting one period ahead of the demand shock, i.e. it is assumed that the regulator has perfect foresight of: (1) the size of the shock, as well as, (2) the timing and during of the shock, with a lead time of one period. Reserve requirements are left unchanged at their original values (Table 7).

Main findings

In general, a one period head-start for the macroprudential regulator, even with perfect foresight, does not statistically significantly impact the ROE – neither across all periods – nor in the subperiod of the negative demand shock when compared to the situation of a passive regulator (see section 4.2) (F18).

One exception to this finding are the two regulatory regimes with 4.5% and 6% minimum reserve requirements for a CAR equal to 4% (F19).

For simulation no. 25-36, the default- and insolvency-frequencies look as follows:

Table 8 summarizes the average means of the default- and insolvency-frequencies (in brackets) of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Table 7: Mean ROEs for simulation no. 25-36.

		Minimum capital requirement:			
Minimum reserve requirement		4%	8%	12%	16%
	3%	9.8%	6.0%	6.1%	5.1%
	4.5%	8.4%*	7.6%	6.4%	5.4%
	6%	11.5%*	7.9%	6.5%	5.5%

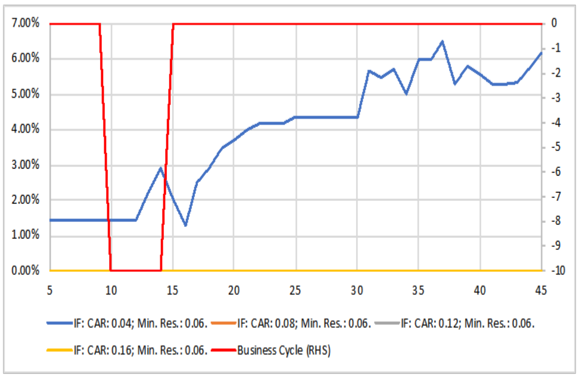

Figure 18: Evolution of IF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

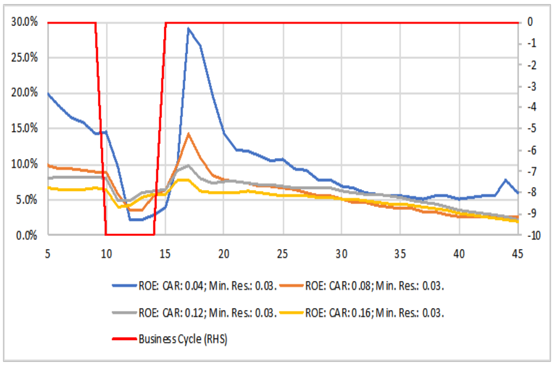

Figure 19: Evolution of ROE over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

Table 8: Mean DFs and IFs for simulation no. 25-36.

		Minimum capital requirement			
		4%	8%	12%	16%
Minimum reserve requirement	3%	4.6% (36.1%)	0.0%* (22.4%*)	0.0% (2.5%)	0.0% (3.3%)
	4.5%	10.5%* (18.5%*)	0.0% (0.5%)	0.0% (0.0%)	0.0% (0.0%)
	6%	25.6%* (15.7%*)	0.1% (0.0%)	0.0% (0.0%)	0.0% (0.0%)

Main findings

The most obvious impact is for the regulatory regime with low minimum capital requirements (CAR=4%) and any configuration for the minimum reserve requirements: in all cases the DFs during the negative demand shock are significantly reduced (F20).

In two of the three cases, this even leads to statistically significant differences when averaged across all time periods (as indicated in table 8) (F21).

Investigating the behavior of the DFs over time, the regulatory regimes with a one-period head-start and perfect foresight lead to significantly higher levels of DFs for the configurations (CAR=4%, min. reserve ratio = 3%), and (CAR=4%, min. reserve ratio = 6%) compared to the situation when the regulator behaves passively (see section 4.2) (F22).

As expected, the impact on DFs is more significant the lower the CAR. That's why regulatory configurations with CAR=8%, 12% or 16% do not show significant changes (F23).

Economic Cycles: Active Macroprudential Regulator: Wrong Foresight One Period Ahead.

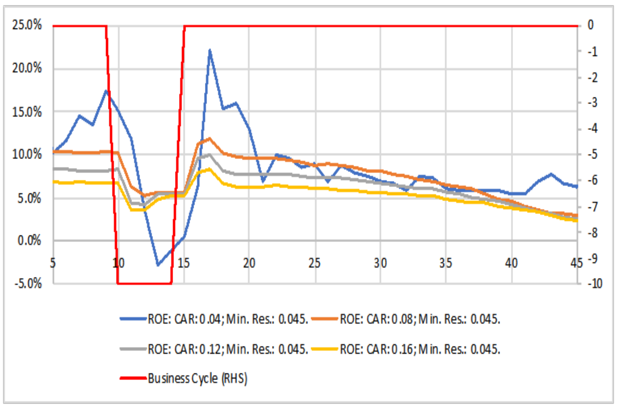

Figure 20: Evolution of ROE over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

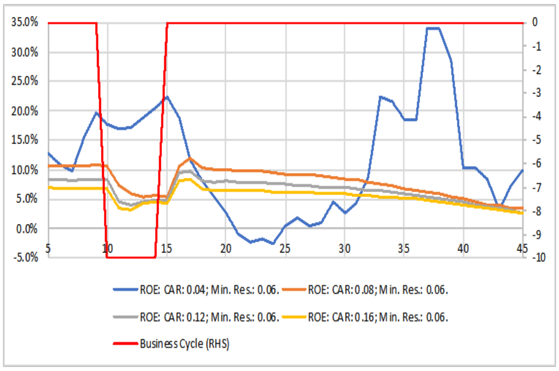

Figure 21: Evolution of ROE over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

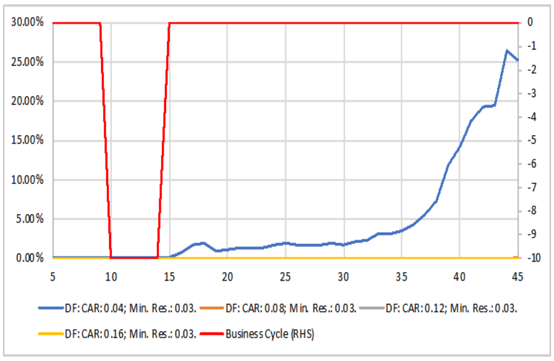

Figure 22: Evolution of DF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

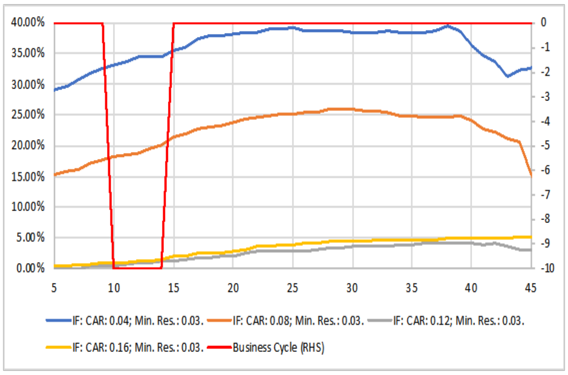

Figure 23: Evolution of IF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

In this section, the results for an economy going through an economic cycle as described in section 4.2 are presented. It is assumed that the regulator acts pro-actively, i.e. adjusts the originally set minimum capital requirements to 150% of their respective values during the demand shock period, starting one period ahead of the demand shock (as in section 4.3). But the regulator thinks an economic upturn will happen and therefore increases the capital requirements. Reserve requirements are left unchanged at their original values (Table 9).

Main findings:

In general, one observes a significant negative impact on ROE during the period of the demand shock for minimum capital requirements 8%, 12% and 16% for all combinations of minimum reserve requirements (F24).

Table 9: Mean ROEs for simulation no. 37-48.

		Minimum capital requirement			
		4%	8%	12%	16%
Minimum reserve requirement	3%	17.0%*	6.8%*	5.7%	4.7%*
	4.5%	7.7%*	5.4%*	3.8%*	2.8%*
	6%	16.1%*	7.6%	6.0%	4.9%*

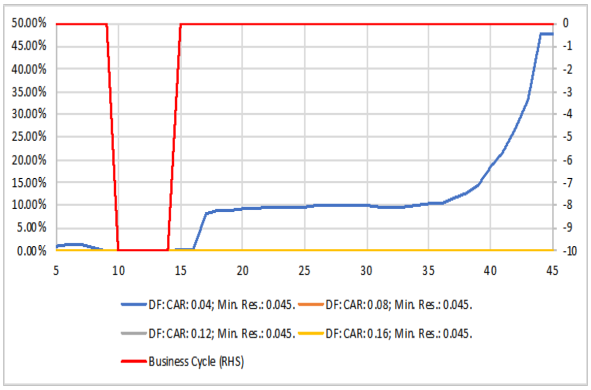

Figure 24: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

For low capital requirements (CAR=4%) the ROE differences are also significant during the demand shock, but for the case of minimum reserve requirements of 4.5%, the differences are positive (F25).

In most cases, the averages over all periods are also significant (as indicated in table 9) (F26).

Table 10 summarizes the average means of the default- and insolvency-frequencies (in brackets) of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Main finding:

A wrongly anticipated business cycle has significant adverse impacts on DFs and IFs (F27).

Economic Cycles: Active Macroprudential Regulator: Correct Foresight with Lead-Time

This section shows the results for an economy going through an economic cycle as described in section 4.2. It is assumed that the regulator acts pro-actively, i.e. adjusts the originally set minimum reserve requirements to 150% of their respective values during the five periods preceding the demand shock, reverting to the original values

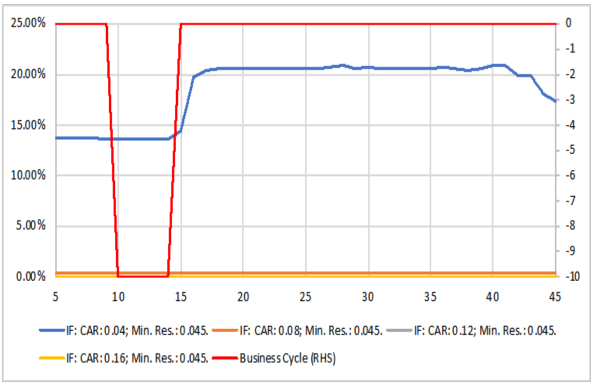

Figure 25: Evolution of IF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

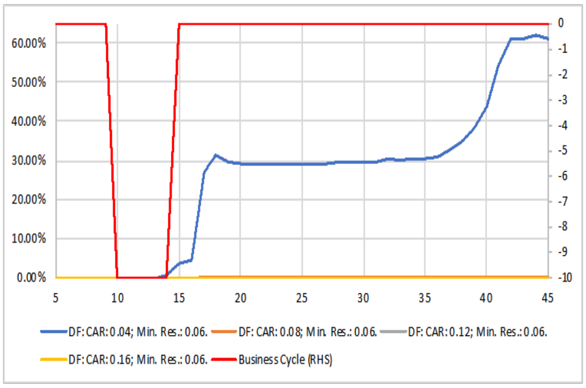

Figure 26: Evolution of DF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

Table 10: Mean DFs and IFs for simulation no. 37-48.

		Minimum capital requirement:			
		4%	8%	12%	16%
Minimum reserve requirement	3%	14.8%* (33.3%*)	10.5%* (13.3%*)	12.4%* (0.6%*)	12.4%* (0.4%*)
	4.5%	12.8%* (0.3%*)	9.0%* (0.0%)	10.9%* (0.0%)	10.6%* (0.0%)
	6%	24.0%* (1.4%*)	12.4%* (0.1%)	12.5%* (0.0%)	12.5%* (0.0%)

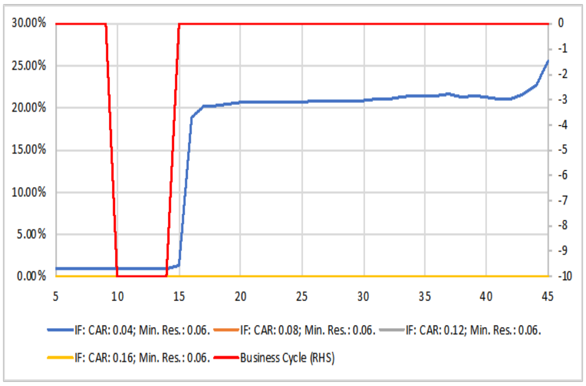

Figure 27: Evolution of IF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

at the start of the demand shock and for all remaining time periods. The regulator has perfect foresight of 1) the timing, 2) the size of, and 3) the direction of the demand shock. Therefore, minimum reserve requirements are increased before the negative demand shock for banks to build up excess reserves which can be drawn upon during times of stress, i.e. the period of the demand shock. Capital requirements are left unchanged at their original values (Table 11).

Table 11: Mean ROEs for simulation no. 49-60.

		Minimum capital requirement			
		4%	8%	12%	16%
Minimum reserve requirement	3%	9.6%	6.2%	6.1%	5.2%
	4.5%	7.4%*	8.3%*	6.5%	5.5%
	6%	7.6%*	8.4%*	6.7%	5.7%

Main findings

For low minimum capital requirements (CAR=4% and 8%) and low original minimum reserve requirements (3%), there is a significant positive impact on ROE during the period preceding the demand shock, i.e. the period of increased minimum reserve requirements (F28).

During the demand shock, there is a significant improvement in ROE for low original minimum reserve requirements (3%) only in low capital requirement regimes (CAR=4%) (F29).

The post-demand-shock-behavior for low original minimum reserve requirements (3%) is very similar to the situation with a passive regulator (section 4.2) resulting in statistically insignificant ROE differences when averaged across all time periods, as is evident from Table 11 (F30).

As the original minimum reserve requirements increase (4.5%, 6%), the positive effects of the increased reserve requirements in the pre-demand-shock-periods as well as during the demand shock become more pronounced for all minimum capital requirements tested (F31).

The higher the minimum capital requirement and the higher the original minimum reserve requirements, the more the ROEs are smoothed out during the period of the demand shock (F32).

The analyses suggest, that this smoothing effect during the shock period comes at the 'cost' of increased return volatility (ROE spike) in the period before the demand shock (F33).

From a pure ROE-perspective it is therefore questionable if this reserves strategy is better compared to the capital strategy of the regulator in section 4.3 (F34).

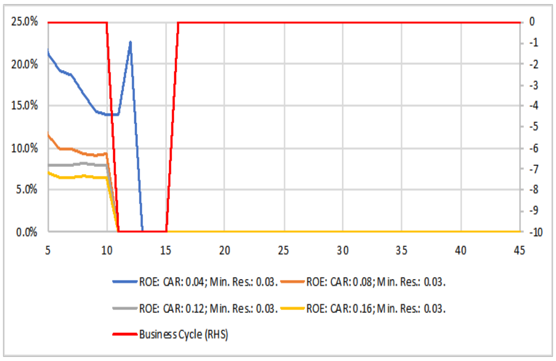

Figure 28: Evolution of ROE over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

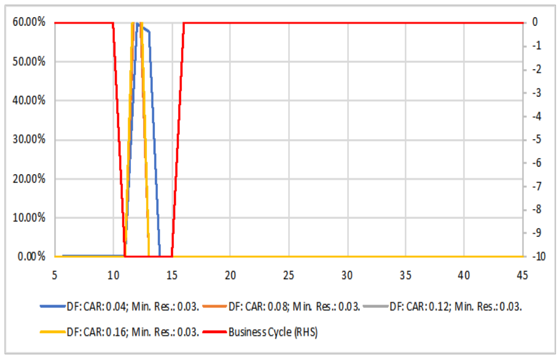

Figure 31: Evolution of DF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

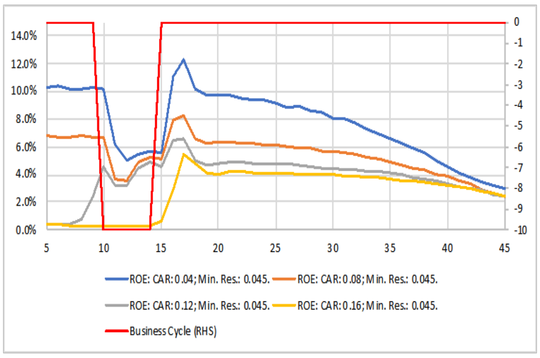

Figure 29: Evolution of ROE over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

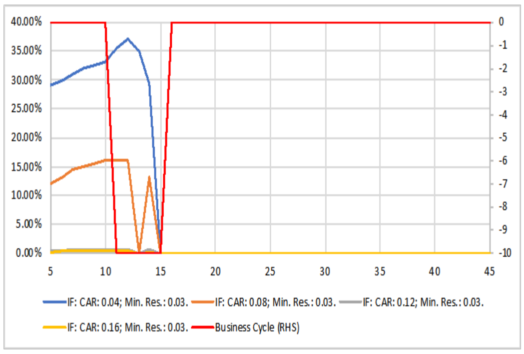

Figure 32: Evolution of IF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

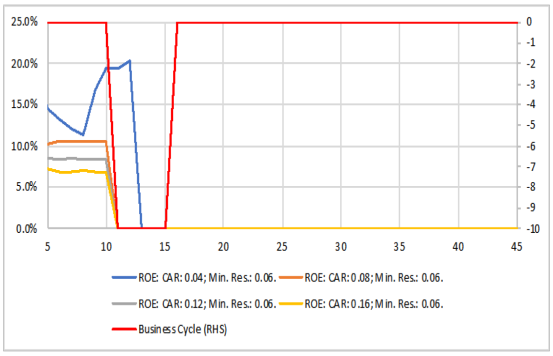

Figure 30: Evolution of ROE over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

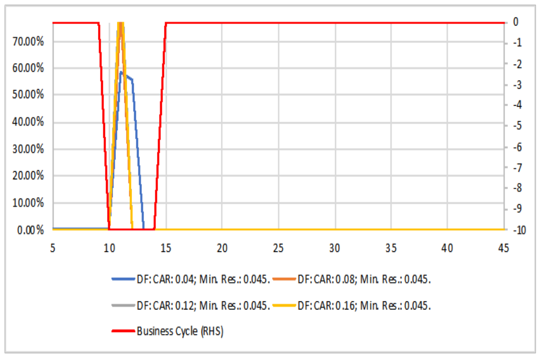

Figure 33: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

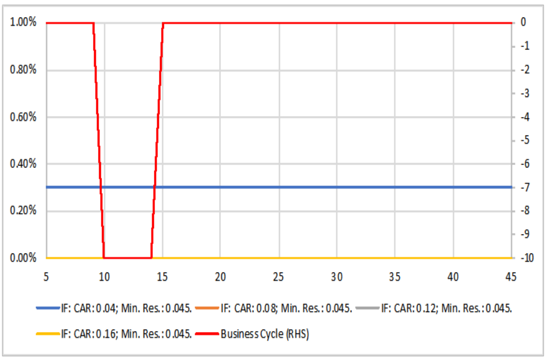

Figure 34: Evolution of IF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

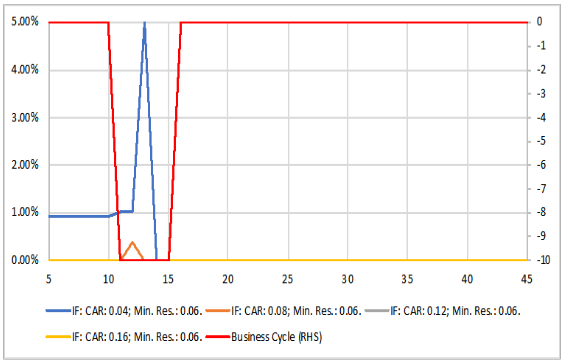

Figure 36: Evolution of IF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

Table 12 summarizes the average means of the default- and insolvency-frequencies (in brackets) of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Main findings

The DF for CAR=4% and an original minimum reserve requirement of 3% during the demand shock period is significantly reduced. Nevertheless, it looks as if the DF-profile of section 4.2 for this regulatory regime has just been shift in time (to the right) with defaults actually significantly increasing and being above those of section 4.2 from period 40 onwards. This explains the significant increase in DF compared to section 4.2 for this regulatory regime when averaged over all time periods (F34).

The results for IF are similarly ambiguous (F35).

In terms of DFs, again, the capital strategy of the regulator in section 4.3 seems to be superior (F36).

Economic Cycles: Active Macroprudential Regulator: Wrong Foresight with Lead-Time.

In this section, the results for an economy going through an economic cycle as described in section 4.2 are presented. It is assumed that the regulator acts pro-actively, i.e. adjusts the originally set minimum reserve requirements to 50% of their respective values during the five periods preceding the demand shock, reverting to the original values at the start of the demand shock and for all remaining time periods. The regulator has perfect foresight of 1) the timing and 2) the size of the demand shock, but getsits direction wrong. Therefore, minimum reserve requirements are decreased before the perceived positive demand shock for banks to investexcess reserves which have to be rebuilt during time of the economic upturn. Capital requirements are left unchanged at their original values (Table 13).

Main finding

A significant increase in the volatility of ROE can be observed in particular before and during the period of the demand shock (F37).

Table 14 summarizes the average means of the default- and insolvency-frequencies (in brackets) of all banks over 100 MC-simulations for periods 5-45 for the different regulatory regimes:

Table 12: Mean DFs and IFs for simulation no. 49-60.

		Minimum capital requirement			
		4%	8%	12%	16%
Minimum reserve requirement	3%	5.5%* (32.1%*)	0.0% (15.7%*)	0.0% (2.8%)	0.0% (1.8%*)
	4.5%	16.6%* (9.7%*)	0.0% (0.3%)	0.0% (0.0%)	0.0% (0.0%)
	6%	44.3%* (7.3%*)	0.1% (0.0%)	0.0% (0.0%)	0.0% (0.0%)

Table 13: Mean ROEs for simulation no. 61-72.

		Minimum capital requirement			
		4%	8%	12%	16%
Minimum reserve requirement	3%	8.2%*	5.3%*	4.3%*	3.7%*
	4.5%	10.9%*	9.2%*	7.2%*	5.7%
	6%	10.2%*	7.9%	6.2%	5.5%

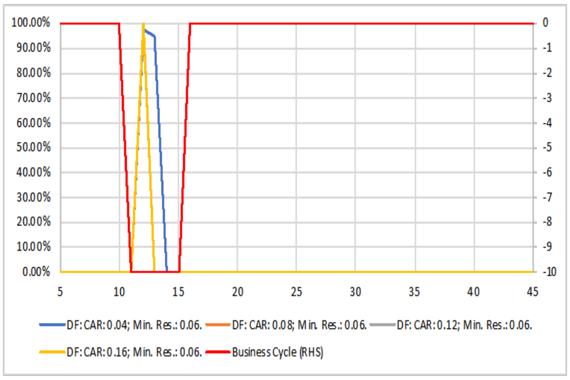

Figure 35: Evolution of DF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

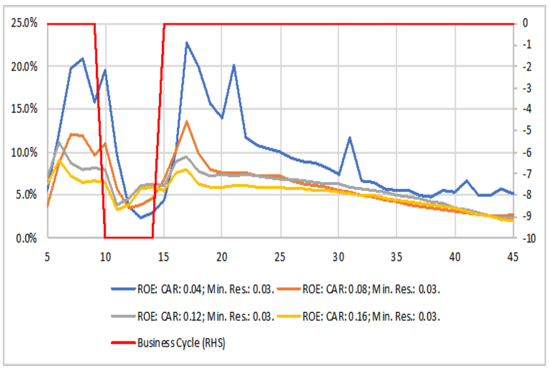

Figure 37: Evolution of ROE over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

Table 14: Mean DFs and IFs for simulation no. 61-72.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	10.0%* (54.7%*)	0.4% (43.0%*)	0.1% (39.4%*)	0.1% (36.3%*)
	4.5%	6.2%* (31.8%*)	0.2% (9.0%*)	0.0% (5.2%*)	0.0% (4.1%*)
	6%	18.7%* (3.4%)	0.0% (0.3%*)	0.0% (0.4%*)	0.0% (0.3%*)

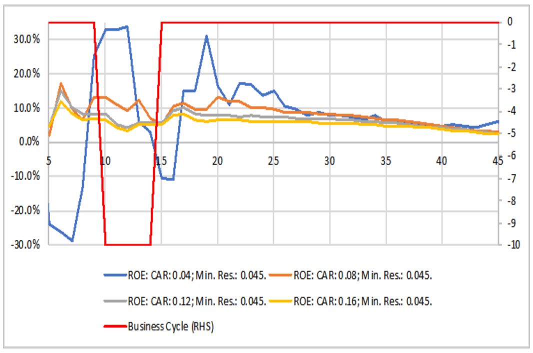

Figure 38: Evolution of ROE over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

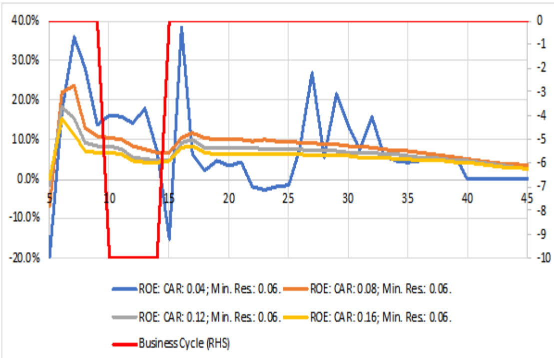

Figure 39: Evolution of ROE over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

Table 11: Mean ROEs for simulation no. 49-60.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	9.6%	6.2%	6.1%	5.2%
	4.5%	7.4%*	8.3%*	6.5%	5.5%
	6%	7.6%*	8.4%*	6.7%	5.7%

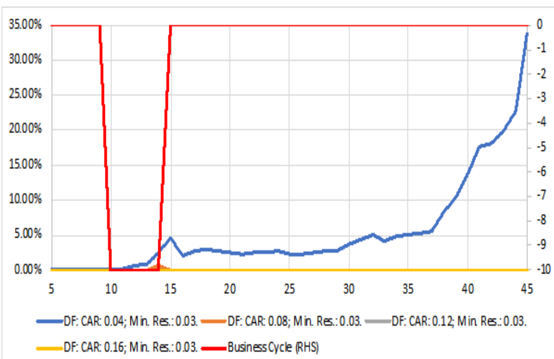

Figure 40: Evolution of DF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

Main finding:

In general, a significant increase of DFs and IFs can be observed during the period of the demand shock, with the exception being reduced DFs for CAR=4% and minimum reserve requirements 6% (F38-F54).

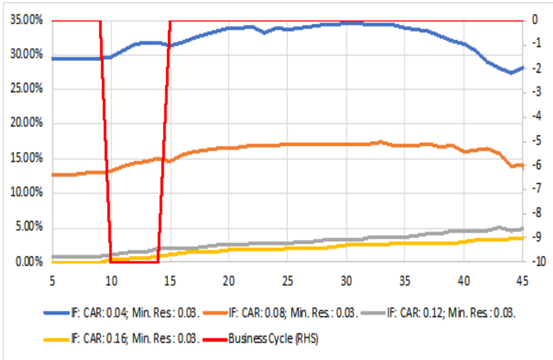

Figure 41: Evolution of IF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

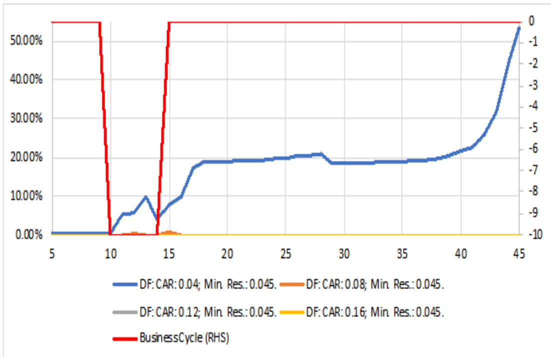

Figure 42: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

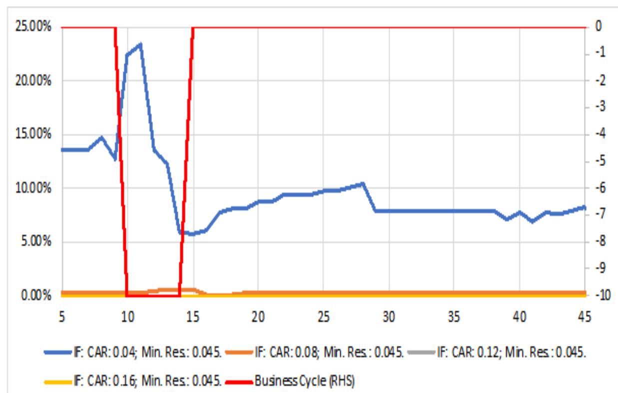

Figure 43: Evolution of IF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

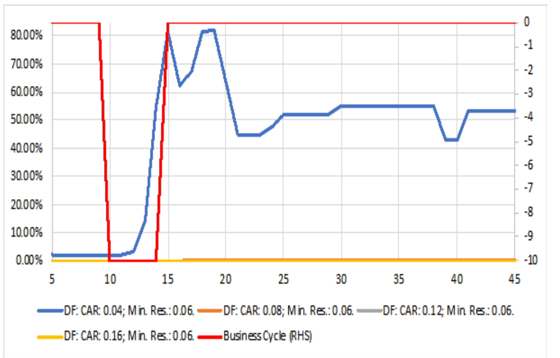

Figure 44: Evolution of DF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

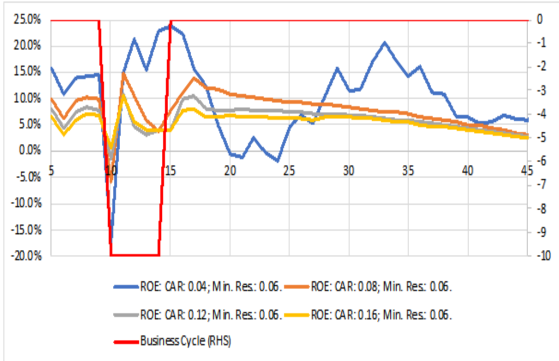

Figure 48: Evolution of ROE over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

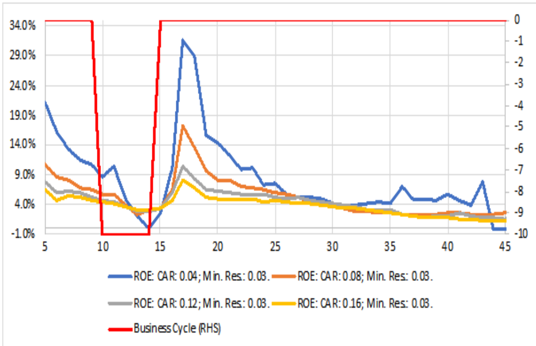

Figure 45: Evolution of IF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

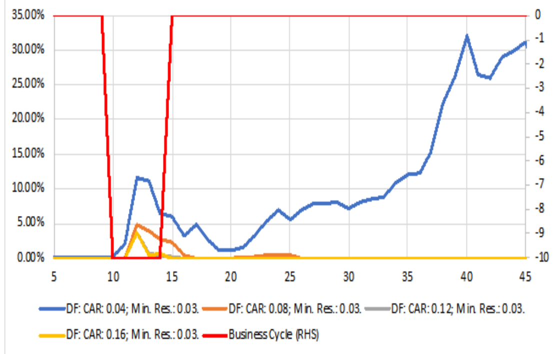

Figure 49: Evolution of DF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

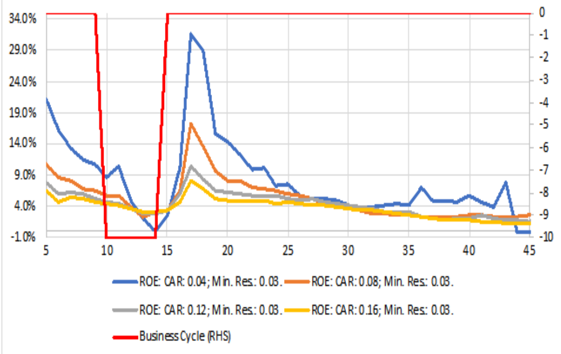

Figure 46: Evolution of ROE over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

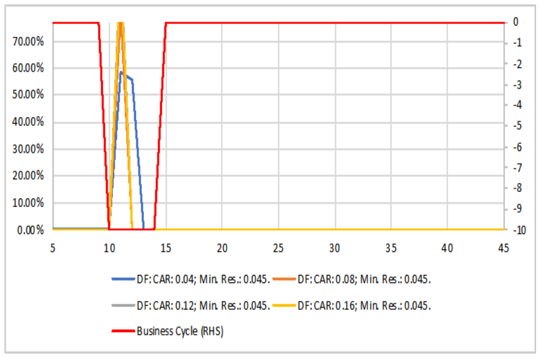

Figure 50: Evolution of IF over time: minimum reserves = 3%; CAR ∈{4%, 8%, 12%, 16%}.

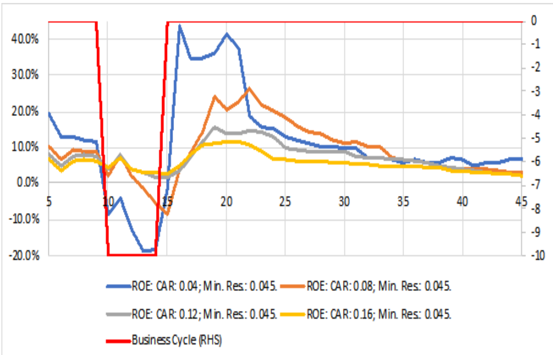

Figure 47: Evolution of ROE over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

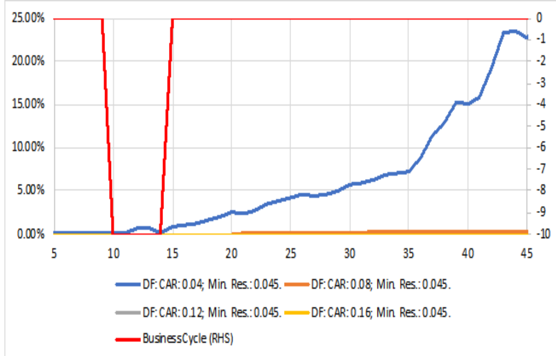

Figure 51: Evolution of DF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

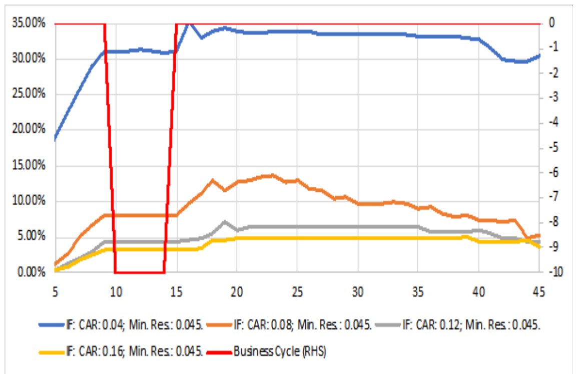

Figure 52: Evolution of IF over time: minimum reserves = 4.5%; CAR ∈{4%, 8%, 12%, 16%}.

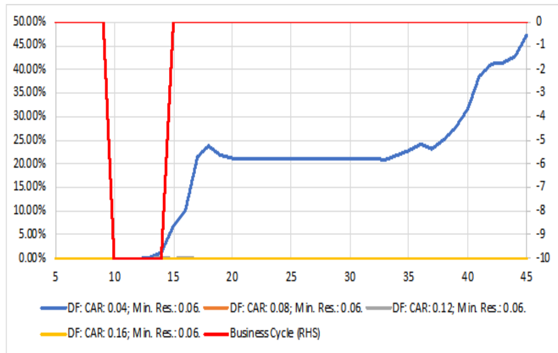

Figure 53: Evolution of DF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

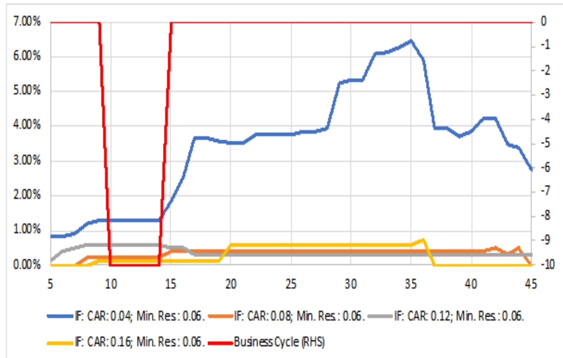

Figure 54: Evolution of IF over time: minimum reserves = 6%; CAR ∈{4%, 8%, 12%, 16%}.

Table 12: Mean DFs and IFs for simulation no. 49-60.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	5.5%* (32.1%*)	0.0% (15.7%*)	0.0% (2.8%)	0.0% (1.8%*)
	4.5%	16.6%* (9.7%*)	0.0% (0.3%)	0.0% (0.0%)	0.0% (0.0%)
	6%	44.3%* (7.3%*)	0.1% (0.0%)	0.0% (0.0%)	0.0% (0.0%)

Summary and Discussion

The simulation results of this study show, that the forecasting ability of the macroprudential regulator is crucial in making counter-cyclical, macroprudential measures effective and efficient. Misjudgments of the economic cycle are likely to make the banking system in particular

Table 13: Mean ROEs for simulation no. 61-72.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	8.2%*	5.3%*	4.3%*	3.7%*
	4.5%	10.9%*	9.2%*	7.2%*	5.7%
	6%	10.2%*	7.9%	6.2%	5.5%

Table 14: Mean DFs and IFs for simulation no. 61-72.

		Minimum capital requirement			
Minimum reserve requirement		4%	8%	12%	16%
	3%	10.0%* (54.7%*)	0.4% (43.0%*)	0.1% (39.4%*)	0.1% (36.3%*)
	4.5%	6.2%* (31.8%*)	0.2% (9.0%*)	0.0% (5.2%*)	0.0% (4.1%*)
	6%	18.7%* (3.4%)	0.0% (0.3%*)	0.0% (0.4%*)	0.0% (0.3%*)

and the financial system in general more fragile. The results show that even properly anticipated economic cycles and corresponding ex-ante changes in the regulatory regime might introduce or exacerbate ROE-cycles. In cases where the regulator's actions smooth out ROE-volatility during times of stress, new, artificial – 'regulatory' / 'policy' – cycles are introduced.

Potential model extensions are manifold, the most obvious ones being briefly highlighted: the study assumed that the negative demand shock is (known) and deterministic. A more realistic model would take the stochasticity of such shocks into account. The hybrid model is designed to only account for reverse-causation. An extension would include feedback mechanisms in the system dynamics part of the model allowing the banking system to impact the real economy. Shifts in monetary policy can also be easily implemented to show (potentially offsetting) effects of monetary policy and macroprudential rules aiming at financial system stability. The ABM of this paper only consists of commercial banks. This can be extended to include other financial intermediaries in order to investigate the effectiveness and efficiency of monetary policy in conjunction with macroprudential rules in world experiencing disintermediation. Lastly, the hybrid model presented is for a closed economy. Extensions to a multi-country-setting are straight forward though potentially computationally extensive.

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