Countercyclical Capital Buffers, Bank Concentration and Macrofinancial Stability in an Agent Based Macro-Financial Framework

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Abstract

This paper examines the impact of countercyclical capital buffers (CCyBs) on financial stability and contributes to the discussion of CCyBs in an agent-based framework. The main focus of this work lies upon the question whether the implementation of CCyBs according to the Basel III framework improves financial stability unconditionally, or at the expense of unintended side-effects. For this purpose, we extend the agent-based model of Riccetti et al. (2021) to investigate the effect of credit-to-GDP-gap based CCyBs in general as well as the effects of varying the smoothing parameter lambda λ of the Hodrick-Prescott (HP) filter within the method of calculating CCyBs. To the best of our knowledge, this study is the first one that investigates systematically how the method of calculating credit-to-GDP-gap based CCyBs may affect macro-financial dynamics and stability in such an agent-based framework.

Keywords: Agent-based modeling, financial stability, financial regulation, macroprudential policy, bank market structure, credit network

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1 Introduction

It is nowadays widely acknowledged that a main reason which led to the Global Financial Crisis (GFC) is the complex network structures within the financial market and the resulting contagion effects (Crotty, 2009; Claessens et al., 2010). The GFC's worldwide repercussions showed also quite clearly how regulatory financial frameworks were insufficient up to that event to address such interconnectedness both at the national as well as at the international levels. Further, various researchers (Borio et al., 2001; Gambacorta and Mistrulli, 2004; Gambacorta, 2008; Repullo et al., 2010) pointed out that the procyclical financial market dynamics generated unintendedly by the existing Basel I and Basel II regulatory frameworks may have exacerbated the financial instability during and in the aftermath of the Global Financial Crisis. Against this background, the objective of Basel III accord was to complement the Basel I and II regulatory frameworks and stabilize the financial system by expanding the regulatory repertoire by macroeconomic (macroprudential) policies (BIS, 2010)that have been developed and implemented step by step by international regulating institutions (Hanson et al., 2011, European Central Bank, 2014) since then. Whereas microprudential policy only considers individual institutions and aims a partial equilibrium regulation within these institutions, Allen and Gale (2009) argue that macroprudential policy take into account the general equilibrium effects within the entire economic system (Allen and Gale, 2009).

In particular, countercyclical capital buffers (CCyBs) are explicitly directed to dampen business fluctuations and thereby make financial institutions more stable (ESRB, 2021). The discussion about the best possible method of calculating CCyBs to dampen procyclicality and to increase bank resilience has not been conclusively answered within the economic literature. Repullo and Saurina (2011) state that in the design of CCBys within the Basel III framework, credit volume is a lagging indicator and not an early indicator of upcoming crises. The credit volume develops at a time lag from the economic development and remains above its long-term trend for a long time in the recession phase. Moreover, Repullo and Saurina (2011) criticize that the time lag is amplified by the fact that CCyBs are only raised as soon as the credit volume exceeds its long-term trend to a certain level. According to Behn et al. (2013), it is uncertain whether the credit-to-GDP gap is suitable as an early warning indicator since the 12-month phase for banks to implement CCyBs, as proposed by BIS and BCBS (2010), also has to be considered. As an alternative to the credit-to-GDP gap, Repullo and Saurina (2011) propose the credit growth as an indicator for calculating the CCyB rate. The fundamental idea of the credit-to-GDP gap and credit growth as indicators is the same but "the additional lag introduced by using deviations of the credit-to-GDP ratio with respect to its trend" (Repullo and Saurina, 2011, p. 15) would not exist if credit growth were taken as an indicator. In a research paper based on historical Spanish financial market data, Ibáñez-Hernández et al. (2015) confirm that credit growth is more appropriate for determining the CCyB rate than the credit-to-GDP gap. Thus and according to Ibáñez-Hernández et al. (2015), a CCyB indicator based on credit growth adapts better to changes in economic cycles. The analysis by Repullo and Saurina (2011) is focused on comparing GDP and credit growth rates to the credit-to-GDP gap with a smoothing parameter of $\lambda = 400,000$ as the underlying indicator for calculating CCyBs within their paper, while Ibáñez-Hernández et al. (2015) compare credit growth rates against different values of λ using Spanish data. Within the agent-based modeling literature, on the other hand, a CCyB mechanism based on the credit-to-GDP-gap and consequently a variation of λ within this method has not yet been addressed and used for agent-based policy simulations.

Our aim is to contribute to the literature of agent-based modeling in the area of macro-prudential policy by investigating systematically how the method of calculating CCyBs may affect macro-financial stability in a medium scale agent-based framework. Since the effect of CCyBs explicitly depends on the state of the business cycle, we believe that the ability to simulate different courses by exogenously specifying the business cycle is a key advantage of the modelling approach by Riccetti et al. (2021) for analysing and testing the effectiveness of CCyBs. For this purpose, we extend the agent-based model of Riccetti et al. (2021) to investigate the effect of CCyBs based on the credit-to-GDP gap in general as well as the effects of varying the smoothing parameter lambda within the method of calculating CCyBs. While Riccetti et al. (2021) consider credit growth rates for calculating CCyBs rates as suggested by Repullo and Saurina (2011), we want to stay closer to the method used and implemented in practice so far which is in line with the Basel III requirements with the credit-to-GDP gap as the underlying indicator for calculating CCyB rates.

The results of our analysis show that the introduction of CCyBs within our medium scale agent-based macrofinancial model has no significant effect on financial stability. The results also suggest that a variation within the CCyB calculation methodology has no impact on financial stability, too. In our model based analysis for potential undetected side effects, such as the influence of CCyBs on the market structure within the banking sector, we did not find any significant effects either.

This paper is structured as follows. Section 2 gives a brief review of the literature. Section 3 describes the agent-based model. Section 4 discusses the dynamics of the model. Section 5 introduces the macroprudential policy instrument of CCyBs and analyzes the effects of the introduction as well as variations within the calculation method of CCyBs on financial stability and bank market structures based on the model proposed while section 6 concludes.

2 Literature Review

Greenwald and Stiglitz (1993) and Grilli et al. (2015) emphasize the importance of credit interlinkages related to financial crises which occur at the microeconomic level. Delli Gatti et al. (2010) took this aspect into account with the "network-based" financial accelerator model, which, in contrast to the financial accelerator model according to Bernanke and Gertler (1989) and Bernanke et al. (1996), also considers credit networks. According to Bernanke and Gertler (1989, 1996), the financial accelerator is a self-reinforcing process related to bank lending and the financial situation of firms. Financially solvent firms with higher net worth are able to lend at more favourable conditions while firms with lower net worth have to bear higher costs of lending. Accordingly, the costs of lending rise in economically bad times, which in turn lowers the demand for credit and ultimately leads to a strengthening of business cycles and vice versa. For Bargigli et al. (2014), the limitation of the neoclassical financial accelerator view is that it assumes a representative agent and ignores the characteristic features of modern economies, such as complex credit linkages and heterogeneous agents. According to Delli Gatti et al. (2010), shocks to individual institutions can undermine the stability of the financial system as a whole due to their interconnectedness, the network structure of the financial system and the actions of other institutions. For example, the default of a borrower leads to a financial deterioration of the lender, who will consequently raise interest rates in order to compensate losses, which in turn leads to a higher burden on all other borrowers and can lead to further defaults. "This is, in a nutshell, the way in which the network-based financial accelerator amplifies a shock" (Delli Gatti et al., 2010, p. 1649).

Baptista et al. (2016) use an agent-based model to analyse the impact of macroprudential policy on the UK housing market. The results suggest that the market for buy-to-let properties in particular amplifies house price cycles and thus their volatility. In addition, a loan-to-income portfolio limit could weaken house price cycles. Cincotti et al. (2012) examine the impact of macroprudential regulation in terms of time-varying capital requirements for banks on financial stability within the agent-based Eurace modelling framework. The results show that time-varying capital requirements are more successful in stabilising the economy and improving economic performance than fixed capital requirements. Cincotti et al. (2012) take the unemployment rate and the growth rate of aggregate credit as the basis for the adaptive adjustment of the dynamic time-varying capital requirements. Riccetti et al. (2021) also examine the impact and effectiveness of macroprudential regulatory policy, in particular of CCyBs, in an agent-based model that builds on the models by Delli Gatti et al. (2010), Riccetti et al. (2013) and Riccetti et al. (2015). In contrast to these papers, Riccetti et al. (2021) exogenously specify the business cycle, which in turn makes it possible to simulate different business cycles and scenarios. The results of Riccetti et al. (2021) suggest that the use of CCyBs can have both stabilising and destabilising effects, depending on the stickyness of the business cycle. Riccetti et al. (2021) conclude that 'the same rule [for determining CCyBs] could be useful in one country and dangerous in another (no "one size fits all")' (p.25).

Catullo et al. (2021) examine the combination of micro- and macroprudential instruments and their impact on the resilience of the financial system. On the macroprudential side, they implement a time-varying capital requirement inspired by a CCyB mechanism which increases capital requirements as the aggregate amount of credit increases. Furthermore, they introduce a mesoprudential policy, which requires higher capital requirements only for more connected banks in order to reduce the impact of contagion effects. They conclude that a combination of micro- and countercyclical policies reduces economic volatility, but leads to more instability in the banking sector in terms of capital structure. The introduction of micro- and mesoprudential policies, on the other hand, strengthens both the banking sector and real economic stability. Introducing the mesoprudential policy, Catullo et al. (2021) exploit the benefits of agent-based modeling by using the granular information of the interconnectedness in a complex banking system to ultimately reduce the impact of contagion effects in case of bank defaults.

In the following section, we describe the model by Riccetti et al. (2021) model, which we extend to include a credit-to-GDP-gap based CCyB mechanism and thus, in contrast to Cincotti et al. (2012), Riccetti et al. (2021) and Catullo et al. (2021), closely follow the BCBS recommendations on the implementation of countercyclical capital buffers.

3 The Model

Our model mainly corresponds to the model with heterogeneous agents and credit networks developed by Riccetti et al. (2021). The model economy is composed of two markets: the goods and the credit market. Firms and banks interact in the credit market, with the former requesting loans to the latter to produce goods, in a way we will discuss in detail below. The goods market consists of consumers and firms. Firms are indexed as $i = 1, 2, ..., I$ and produce a homogenous good through a simple production function that transforms a firm i's total financial capital $K_{i,t}$ into consumption goods $Y_{i,t}$, i.e.

$$Y_{i,t} = \phi K_{i,t}, \tag{1}$$

where $\phi > 1$ is a parameter uniform across firms.

In the same spirit as Greenwald and Stiglitz, 1993 (see also Delli Gatti et al., 2005, Delli Gatti et al., 2010, Catullo et al. (2021) and Riccetti et al. (2021), we assume that firms face in each period a stochastic operating profit $op_{i,t}$ per unit of their output, which can be both positive or negative and includes all costs of production besides financial costs. The operating profit $op_{i,t}$ is a random number drawn by $N_{i,t}(\alpha_t, \sigma_{op})$ where α_t is specified as an autoregressive AR(1) process with

$$\alpha_t = \alpha_0 + b \cdot (\alpha_{t-1} - \alpha_0) + \varepsilon_t, \tag{2}$$

where the innovation term ε_{it} is assumed to follow a normal distribution with zero mean and standard deviation, i.e. $\varepsilon_t \sim N(0, \sigma_{cyc})$.[1] A high stochastic operating profit per unit of output implies periods of high demand and high prices, while a low or negative profit implies periods of low demand and low prices, which ultimately increases the likelihood of firms going bankrupt.

[1] The advantage of implementing firms' profits with an AR(1) process is that it allows us to simulate and thus analyze different courses of business cycles that can be calibrated to country-level data. The demand side of the model is thus extremely simplified and assumed to be fully reflected by the realization of the stochastic price process, which could be interpreted as describing demand shocks. Note that the parameter values α_0, b, and σ_{cyc} can be calibrated on country-level data to simulate different types of business cycles. Since the GDP business cycle of Germany can be adequately represented by an AR(1) process as shown by Riccetti et al. (2021) using German GDP data from the Federal Reserve Economic Database from 1961:1 to 2018:3, we will set the autoregressive parameters of $b = 0.84$, $\alpha_0 = 0.02$ and $\sigma_{cyc} = 0.005$ in our numerical simulations.

The total profit of firm i is computed as the operating profit per unit of output $op_{i,t}$ multiplied by the level of production $Y_{i,t}$ less credit costs:

$$\Pi_{i,t} = op_{i,t} \cdot Y_{i,t} - r^F_{i,t} \cdot B_{i,t}. \tag{3}$$

where $B_{i,t}$ denotes the firm i's outstanding loan amount of loan and $r^F_{i,t}$ the interest rate charged by bank z to firm i.

In every period the new profits $\Pi_{i,t}$ are added to the firm i's current net worth $A_{i,t}$ determining the net worth in the next period $t+1$, i.e.

$$A_{i,t+1} = A_{i,t} + \Pi_{i,t} \tag{4}$$

If the losses (negative profits) are higher than the previous net worth $-\Pi_{i,t} > A_{i,t}$, so that the new net worth becomes negative $A_{i,t+1} < 0$, firm i goes bankrupt and leaves the market. In order to keep the number of firms constant within the model, we assume that in the event of bankruptcy a new firm will automatically enter the market, as we will discuss in detail in Section 3.2.

As in Riccetti et al. (2021), we assume that firms decide upon their target level of production and their financial structure independently. Further, we assume that firm i will increase its target production in period t if it received positive operating profits $op_{i,t-1}$ in the previous period. In case of negative operating profits $op_{i,t-1} \leq 0$ or if they were equal to zero in the previous period $t-1$, firm i will decrease its production target in t:

$$Y^*_{i,t} = \begin{cases} Y^*_{i,t-1} \cdot [1 + U(0,\tau)] & if \quad op_{i,t-1} > 0 \\ Y^*_{i,t-1} \cdot [1 - U(0,\tau)] & if \quad op_{i,t-1} \leq 0. \end{cases} \tag{5}$$

The parameter $0\% \leq \tau \leq 10\%$ is setting the maximum randomly percentage change of the target output of firm i. The total capital target needed to produce the output target can be computed by inverting equation (1):

$$K^*_{i,t} = Y^*_{i,t}/\phi.$$

In order to increase the return per unit of net worth, firms try to adjust their capital structure.

The firms' capital structure is represented by the leverage ratio $L = \dfrac{B}{A}$. According to the (dynamic) trade-off theory,[2] firms set their target leverage as follows:

$$L^*_{i,t} = \begin{cases} L^*_{i,t-1} \cdot [1 + U(0,\tau)] & if \quad \phi \cdot op_{i,t-1} > r_{i,t-1} \\ L^*_{i,t-1} \cdot [1 - U(0,\tau)] & if \quad \phi \cdot op_{i,t-1} \leq r_{i,t-1} \end{cases} \tag{6}$$

[2]For a more detailed discussion of the dynamic trade-off theory, see for instance Riccetti et al. (2013).

where $r_{i,t-1}$ represents the interest rate paid by firm i on its bank loans in the last period $t-1$. If the profit per unit of capital is greater than the interest paid per unit of credit, firm i increases its leverage, and vice versa.

The target capital $K^*_{i,t}$ and target leverage $L^*_{i,t}$ determine the firm i's net worth $A^*_{i,t}$:

$$A^*_{i,t} = \frac{K^*_{i,t}}{1 + L^*_{i,t}} \tag{7}$$

After calculating their respective target net worth, firms compute the amount of dividends they will pay in order to adjust their respective capital structure:

$$Div_{i,t} = max(A_{i,t-1} - A^*_{i,t}, 0). \tag{8}$$

Accordingly, dividends are calculated as the difference between firm i's net worth in the previous period $t-1$ and the target net worth in period t. If the net worth in $t-1$ is below the target net worth, firm i will pay no dividends. After the calculation and distribution of dividends, there is a new net worth $A_{i,t} \leq A^*_{i,t}$, which will be used by firms for the production of goods in the current period.

Based on the new net worth $A_{i,t}$ after the dividend payout, firm i calculates its target debt $B^*_{i,t}$:

$$B^*_{i,t} = min(K^*_{i,t} - A_{i,t}, 10 \cdot A_{i,t}), \tag{9}$$

which is determined by the difference between the target capital $K^*_{i,t}$ and the net worth $A_{i,t}$ with a maximum of ten times the net worth. We follow Riccetti et al. (2021) and assume that banks limit credit when firms are excessively leveraged. Therefore, firm i receives an amount of credit on the credit market which is less than or equal to its credit demand $B_{i,t} \leq B^*_{i,t}$.

3.1 Firm-Bank Interaction

The focus and dynamics of this model are based on a decentralized credit market and the interaction between firms and banks, which are indexed as $z = 1, 2, ..., Z$. The credit relationships arise within an endogenous credit matching process: In each period, firms enter the credit market in random order and are faced with the credit offer of all Z banks. The banks all offer the same interest rate and firms choose the bank with the largest credit offer to fulfill their credit demand. Firm i will then select the bank that offers the largest amount of credit. If the loan offer of the selected bank is lower than the firm i's demand for credit, the firm will take out another loan from the bank with the second largest credit supply. This process continues until the credit demand of firm i is satisfied, until the credit supply B_t of all Z banks is exhausted, or until a bank only offers less than 1% of firm i's original credit demand.[3]

The banks' total credit supply is limited by two regulatory conditions:

$$B_{z,t}^{max} = min(A_{z,t} \cdot \left(\frac{100}{6 + CCyB_t}\right); \qquad 0.25 \cdot A_{z,t}). \tag{10}$$

We thus assume that the maximum credit supply of banks will be restricted by regulatory minimum capital requirements (see for instance Cincotti et al., 2012, Bargigli et al., 2014, Dawid and van der Hoog, 2015 and Riccetti et al., 2021) as well as a countercyclical capital buffer ($CCyB$) according to the Basel III framework.[4] Therefore, bank z has to comply with the minimum capital requirements of $6\% + CCyB_t$ of its net worth. The determination of the CCyB rate will be explained in more detail in section 4.1. Moreover, bank z is restricted to lend a maximum of 25% of its net worth to a single firm. Nevertheless, the banks have the option at any time of borrowing money without restriction from the central bank at a fix refinancing interest rate in order to meet the demand for credit within the framework of the regulatory restrictions.

The interest rate paid by firm i is determined as follows:

$$r_{i,t}^F = r^{CB} + rp_{i,t} + 0.1 \cdot c + \mu, \tag{11}$$

where c is a fix cost- and μ a fix mark-up parameter, and the policy rate set by the central bank r^{CB} is a fixed parameter and equals the loan interest rate banks can borrow capital from the central bank, pay on deposits or can refinance themselves via the interbank market.[5] These costs of borrowing are given in an 1:1 ratio to firms. Further, the firm-specific risk premium $rp_{i,t}$ is

$$rp_{i,t} = PD_{i,t}^e \cdot \left(1 + \frac{bad_{t-1}}{B_{t-1}}\right) \tag{12}$$

where $PD_{i,t}^e$ is the expected probability of default of firm i in period t and $\frac{bad_{t-1}}{B_{t-1}}$ represents the share of aggregated non-performing loans of the loans given to all firms in period $t-1$.

[3] Like Riccetti et al. (2021), we assume that firm i is not interested in such small loans.

[4] In the baseline scenario we set $CCyB = 0$.

[5] Since r^{CB} is a fixed parameter, it does not matter in this model whether the banks use the central bank, deposits or the interbank market to refinance themselves.

We assume that the expected probability of default of firm i corresponds to its probability of default in the previous period, i.e.

$$PD^e_{i,t} = PD_{i,t-1},$$

which is calculated based on a cumulative distribution function of $N_{i,t}(op_t, \sigma_{op})$ and the expression $\dfrac{r^F_{i,t-1} \cdot L_{i,t-1} - 1}{\phi \cdot (1 + L_{i,t-1})}$, which corresponds to firm i's default probability in the previous period at a leverage of $L_{i,t-1}$ and an interest rate of $r^F_{i,t-1}$.[6]

The individual credit relationships between firms and banks create a credit network in which all agents are intertwined. If the shock or the losses of a firm are high enough and the firm can no longer meet its interest payments to the bank, the firm goes bankrupt, inevitably causing losses for the connected bank(s) as well, and possibly making the bank itself going bankrupt. Moreover, the interest rates will increase in the next period due to a higher risk premium to compensate the losses incurred. If a corresponding partner bank or firm defaults, this mechanism ensures a direct financial effect on both sides, namely the borrower and the lender.

3.2 Bankruptcies and Bank Entries

The newly entering firm is attributed with a net worth equal to the median net worth of all surviving firms.

As just discussed, the bankruptcy of a firm has a direct influence on the net worth of the bank associated with that firm, as in this case the former would no longer meet its credit obligations to the latter. Similar to Riccetti et al. (2021), we assume that in such a case the bank will be the first creditor to be served by the bankrupt's estate and potentially therefore only lose a part of the outstanding loan amount. The loan recovery ratio (LRR) is calculated as:

$$LRR_{i,t} = -max\left(\frac{A_{i,t} + \Pi_{i,t}}{B_{i,t}} - le; -1\right). \tag{13}$$

where the parameter le represents a percentage of legal expenditures in the case of bankruptcy.

The amount of defaulted loans $\psi_{z,t}$ of bank z is then:

$$\psi_{z,t} = B_{z,i,t} \cdot LRR_{i,t}. \tag{14}$$

[6]Following Riccetti et al. (2021) we set $\sigma_{op} = 0.05$.

which can be calculated by the product of bank z's given loan to firm i and the $LRR_{i,t}$ of firm i.

As well as the profits of the firms, the profits of banks are calculated in each period:

$$\Pi_{z,t} = \sum r^F_{z,i,t} \cdot B_{z,i,t} - r^{CB} \cdot D_{z,t} - c \cdot A_{z,t} - \psi_{z,t}. \tag{15}$$

The profit of bank z is composed of four components. The first is the sum of all given loans $B_{z,i,t}$ of bank z, multiplied by the respective interest rates $r^F_{i,t}$ charged to the corresponding firms. This sum can be considered as bank z's revenue. The second component represent the refinancing costs. According to Riccetti et al. (2021), we assume that all banks pay the same interest rate r^{CB} for refinancing via the central bank or deposits and $D_{z,t} = \sum B_{z,i,t}$. The parameter c in the third component represents to the bank's fixed cost, which depend on the size of the bank, measured in terms of net worth. Finally, the fourth component represents the sum of irrecoverable credit claims $\psi_{z,t}$. These irrecoverable credit claims are calculated as the sum of all loans granted from bank z to defaulted firms in period t multiplied by the respective LRR rate as described in equation (14).

After calculating the profits of bank z, the new net worth $A_{z,t+1}$ of bank z can be calculated as:

$$A_{z,t+1} = A_{z,t} + \Pi_{z,t}. \tag{16}$$

The new respective net worth in $t + 1$ is the result of a banks' net worth in t plus the banks' profits in t. If the net worth turns negative $A_{z,t+1} < 0$ the bank goes bankrupt. This is the case, if the negative profits are greater than banks' net worth: $-\Pi_{z,t} > A_{z,t}$. Similar to a bankrupt firm, a new bank enters the market in the event of the bankruptcy of a bank in order to keep the number of banks constant. This entering bank is initially endowed with a net worth equal to the median net worth of all surviving banks (Riccetti et al. (2021)).

4 Validation

According to Schasfoort et al. (2017), the volatility, autocorrelation and cross-correlation structures of several aggregated macroeconomic variables of interest are examined for the validation of the underlying model. For this purpose, we check the properties of the simulated time-series data with the properties of empirical data for the relevant variables. Since the model consists of both a credit and a goods market and the focus of this paper lies on the mechanism of the macroprudential instrument of CCyBs, the following variables are used for the validation: GDP, credit volume and the credit-to-GDP ratio.

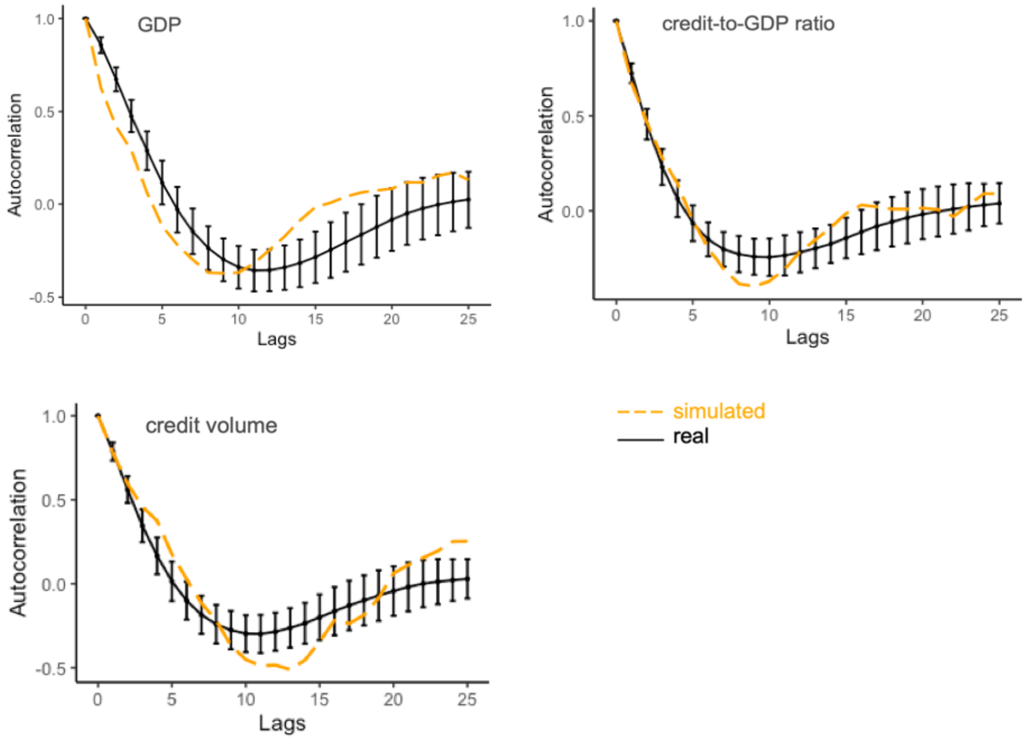

Figure 1: Autocorrelations of the de-trended empirical German and simulated time series of GDP (top left), credit-to-GDP ratio (top right) and credit volume (bottom left) with lags up to 25. Data are from the FRED data base for the period from 1991:1 to 2021:2.

For the baseline scenario, we run a Monte Carlo simulation with 100 simulations of 400 time periods each, using the parameter values reported in Table 1 and truncating the first 100 periods of the initialisation phase. The black lines in Figure 1 show the simulated data of the baseline scenario with the corresponding standard deviations. The y-axes indicate the values of the autocorrelations between 0 and 1, while the x-axes represent the *lags* from 0 to 25. The plot of autocorrelations show the relationship between the value of a variable in time t and the value of the same variable in a prior time at $t - lags$. Figure 1 shows that the autocorrelation structures of the simulated (artificial) variables are close to those of the real German data.[7]

[7] We choose Germany as the reference country given its predominant role in the European Union. A possible

Table 1: Baseline Parameter Values

Parameter	Symbol	Value
Production function parameter	ϕ	3
Speed adjustment parameter	τ	0.1
Fixed cost parameter	c	0.1
Mark-up parameter	μ	0.01
Central bank interest rate	r^{CB}	0.01
Cost parameter for legal expenditures	le	0.1

Figure 2 shows the cross-correlation between the macroeconomic variables of credit volume and GDP, which are crucial for the model and form the basis for the macroprudential instrument of CCyBs. The basic structure of the empirical cross-correlation between German credit volume and German GDP can be replicated by the model. However, while the empirical German data show a maximum at $lag = 8.5$, the maximum of the cross-correlation in the simulated data is at $lag = 0$. This indicates a mutual influence of the two variables in the German data that is offset in time. Since GDP in our model is directly dependent on the development of the simulated credit volume due to equation 1, the maximum of the simulated cross-correlation is at $lag = 0$ and has no time offset. One reason for the time lag in the real cross-correlation structure could be the different types of credit. Our model does not distinguish between consumer credit, which increases output and GDP immediately and without a lag, and investment credit.

extension of the present framework could be a systematic analysis of the capability of the present framework to fit the macrofinancial dynamics of the other countries both of the European Union as well as from the rest of the world.

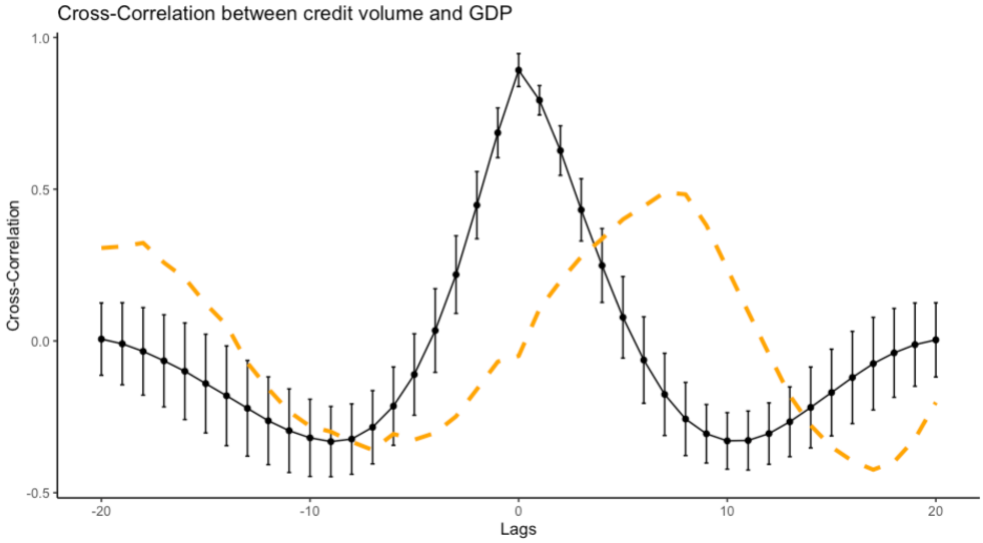

Figure 2: Cross-correlation structure between German credit volume to the non-financial sector and German GDP (orange line) as well as simulated credit volume and simulated production output with corresponding standard deviations (black line).

Since the development of GDP and credit volume are important variables for determining the CCyB rate, we also compare the volatility of the simulated GDP and the credit-to-GDP ratio with the real German data. For this purpose, we follow the approach by Schasfoort et al. (2017) and Caiani et al. (2016) by comparing the cyclical components of the simulated and empirical time series. To compute the cyclical component of the time series, we use the Hodrick-Prescott (HP) filter with a smoothing parameter of $\lambda = 1,600$, as recommended by Drehmann et al. (2010) for quarterly data.

The validation shows that the model is able to reproduce several essential characteristics of the real empirical data in order to conduct different policy experiments on the macroprudential instrument of CCyBs.

5 Macroprudential Policy

In this section, we discuss and specify in more detail the macroprudential instrument of CCyBs to investigate whether and how the introduction of such a buffer can smooth the business cycle, increase the loss-bearing capacity of the banking sector and thus enhance financial stability within this model.

5.1 The Countercyclical Capital Buffer (CCyB)

The introduction of CCyBs is intended to oblige banks to build up equity in economically strong times, which they can use again in economically weaker times (Cincotti et al., 2012; Tente et al., 2015). As an indicator of economically strong or weak times, and ultimately also for determining the CCyB rate, BIS and BCBS (2010) use the credit-to-GDP gap.

The credit-to-GDP gap is calculated as the deviation of the credit-to-GDP ratio from its long-term trend:

$$GAP_{i,t} = RATIO_t - TREND_t. \tag{17}$$

While the $RATIO_t$ is computed as the sum of the aggregated loans to the private sector divided by the aggregated output (GDP), the long-term trend of the credit-to-GDP ratio is calculated by applying the HP-filter with a smoothing parameter of $\lambda = 400,000$ to the RATIO variable.

In accordance with the Basel III framework, the following reference values were set for the calculation of the CCyB rate:

$$CCyB_t = \begin{cases} 0\% & if \quad GAP_{t-1} \leq 2\% \\ 0.3125 \cdot GAP_{t-1} - 0.625 & if \quad 2\% < GAP_{t-1} \leq 10\% \\ 2.5\% & if \quad GAP_{t-1} > 10\%. \end{cases} \tag{18}$$

The CCyB rate can range between 0% and 2.5%. If the credit-to-GDP gap GAP_{t-1} is less than two percent in the previous period, the CCyB rate remains at zero percent and no additional capital requirements are imposed on banks. If the gap GAP_{t-1} is more than 10%, the CCyB rate increases to its maximum of 2.5%. If $2\% < GAP_{t-1} \leq 10\%$, the CCyB rate is determined by linear interpolation between its minimum value of 0% and its maximum value of 2.5%.

5.2 Impact of CCyBs on Financial Stability

In this section, we implement the macroprudential tool of CCyBs into our baseline model in order to compare the results of the baseline simulation before and after the CCyB mechanism was introduced.

While BIS and BCBS (2010) recommend a smoothing parameter of $\lambda = 400,000$ within the HP-filter for calculating CCyBs, which is in line with the empirical analyses of Drehmann et al. (2010), we also examine the impact of varying λ within the method of calculating CCyBs on financial stability. For this purpose, we examine the values of λ recommended by Drehmann et al. (2010) and Ravn and Uhlig (2002) for different lengths of credit cycles: $\lambda = 1,600, \lambda = 25,000, \lambda = 125,000$ and $\lambda = 400,000$.[8]

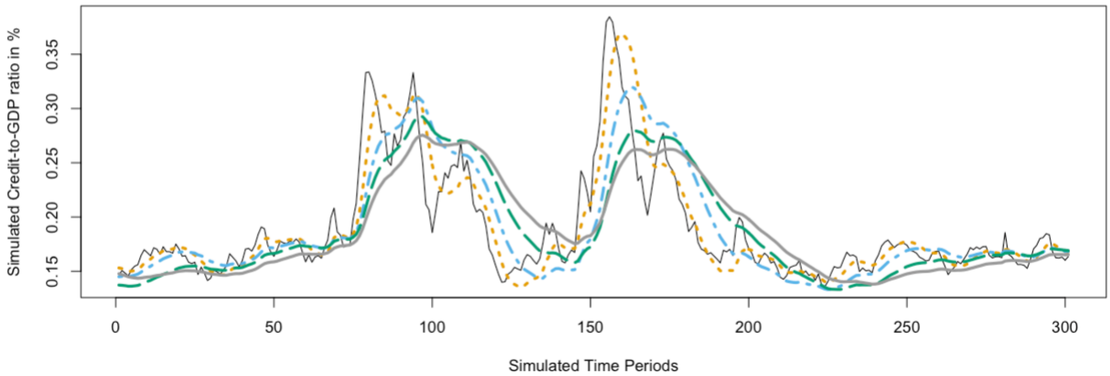

Figure 3: Credit-to-GDP ratio (black solid line) and development of the trend components of the Credit-to-GDP ratio with: $\lambda = 1,600$ (orange dotted line), $\lambda = 25,000$ (blue dot-dashed line), $\lambda = 125,000$ (green long-dashed line) and $\lambda = 400,000$ (grey solid line) within a single simulation run without CCBys from $t = 101$ to $t = 400$.

In order to illustrate the effect of a change of λ, figure 3 shows the evolution of the credit-to-GDP ratio for a single simulation run without CCyBs. The x-axis shows the time periods, while the y-axis represents the ratio of aggregated credit volume to aggregated output. In addition, the figure shows the development of the trend component using the HP-filter of the credit-to-GDP ratio for the parameter values $\lambda = 1,600, \lambda = 25,000, \lambda = 125,000$ and $\lambda = 400,000$. The effects of varying the smoothing parameter λ relate in particular to the development of the trend component, the credit-to-GDP gap and consequently the determination of the CCyB rate. The credit-to-GDP gap results from the distance between the credit-to-GDP ratio and the development of the respective trend component, which are displayed in different colours for the various values of λ. It can be seen that the higher the smoothing parameter λ, the smoother the trend component. In particular, the sharp increase in the credit-to-GDP ratio from period $t = 75$ as well as the second sharp increase from period $t = 138$ show that the higher the smoothing parameter λ, the longer it takes

[8]For a more detailed discussion about determining the values for λ within the HP-filter with respect to different lengths of credit and business cycles, see Drehmann et al. (2010) and Ravn and Uhlig (2002).

for the credit-to-GDP ratio to exceed its long-term trend and to fall below it again at the same time. In terms of the CCyB-mechanism, this implies that the CCyB will be activated (released) at a later point in time during a boom phase (downturn), compared to lower values of the smoothing parameter λ. This confirms the criticism and argumentation by Repullo and Saurina (2011) that the credit-to-GDP gap is a lagging indicator for calculating CCyBs.[9]

In order to analyse the effect of the introduction of a CCyB mechanism and a variation of the smoothing parameter λ within the CCyB calculation method on financial stability, we compare various macroeconomic key variables before and after the introduction of the CCyB mechanism and testing those for significance. The results of the Monte Carlo simulation in table 2 show the means and average standard deviations across all 100 Monte Carlo simulations for the baseline scenario, as well as the scenarios with $\lambda = 1,600, \lambda = 25,000, \lambda = 125,000$ and $\lambda = 400,000$ after introducing the CCyB mechanism.

Apart from CCyBs rates, which differ significantly from the baseline scenario without CCyB due to their introduction, economic growth and its volatility, credit growth and its volatility as well as the share of defaulted loans are not significantly by the introduction of CCyBs. Only the scenario with λ =125,000 shows a significant increase in the share of defaulted banks. However, the increase in the share of defaulted banks in this scenario has no further impact on financial stability, since lending and output growth are not affected by the introduction of CCyBs. A possible reason for that could be due to a shift in lending from larger banks to smaller banks within the banking sector as a result of the introduced CCyBs. In our model there are different channels of transmision that accompany the introduction of CCyBs. To comply with stricter capital requirements, there are several transmission channels available for banks (Cohen, 2013). Banks can use these channels on both the asset and liability side of their balance sheets.

In our model, banks can react to increased capital requirements by reducing dividend payouts with a time lag (equation 8) or by immediately restricting their lending. Therefore, an increase in capital requirements leads to a direct reduction in the supply of credit by banks, assuming that the amount of capital remains unchanged. Given a constant credit demand in this scenario, higher capital requirements tend to allow smaller banks to relatively lend more,

[9] While Repullo and Saurina (2011) propose growth rates as an alternative for calculating the CCyB rate, we want to stay to the currently recommended and used calculation method under Basel III and analyse a variation of the smoothing parameter λ within the HP-filter.

Table 2: Effects of introducing CCyBs and varying the smoothing parameter λ

Parameter	baseline	$\lambda = 1,600$	$\lambda = 25,000$	$\lambda = 125,000$	$\lambda = 400,000$
output growth	0.994%	1.008%	1.019%	1.019%	1.027%
	(8.014%)	(8.052%)	(7.941%)	(8.072%)	(8.113%)
credit growth	2.662%	2.667%	2.656%	2.729%	2.749%
	(18.719%)	(18.671%)	(18.483%)	(18.836%)	(18.925%)
share of defaulted banks	0.241%	0.258%	0.258%	0.283%**	0.260%
share of defaulted loans	2.324%	2.324%	2.310%	2.315%	2.311%
equity ratio of banks	6.538%	6.563%	6.607%	6.576%	6.523%
CCyB rate	0.000%	0.391%***	0.582%***	0.671%***	0.669%***

Note: Means and standard deviations (in brackets) over 100 Monte Carlo Simulations.
*** p<0.01, ** p<0.05, * p<0.1.

measured in terms of aggregated credit supply, as larger banks are unable to meet credit demand earlier in the credit-matching process. Hence, this leads to a shift in lending and could have an impact on the market structure in the banking sector, which we will discuss in the following section.

5.3 Macroprudential Policy and Bank Market Structure

In the context of macroprudential policy, the network and market structure within the banking and credit market also plays an important role since the introduction of the macroprudential instrument of CCyBs were intended in particular to improve the stability of institutions in order to protect them from default and thus prevent contagion effects on the financial markets (BIS and BCBS (2010)). Hence, the academic research about the impact of market structure and market concentration on financial stability is essential. The literature in this context can be divided into two different views on the question of whether bank concentration has a stabilising or destabilising effect on financial stability: the concentration-fragility view and the concentration-stability view (Mirzaei et al. (2013)).[10]

Nevertheless, whether the concentration-stability view or the concentration-fragility view

[10]For a more detailed discussion about the concentration-fragility and the concentration-stability view, see e.g. Boyd and De Nicoló (2005), Beck et al. (2006), Jiménez et al. (2013), Berger et al. (2009), Mirzaei et al. (2013).

is true, if macroprudential regulation affects the market structure of the banking sector, this needs to be taken into account in the design of macroprudential policy. Otherwise, macroprudential regulation could lead to a destabilisation of financial markets. In this case, the use of macroprudential regulation would have a counterproductive effect on the goal of macroprudential regulation - the increase of financial market stability - and favour the emergence of a financial market crisis due to a self-reinforcing effect.

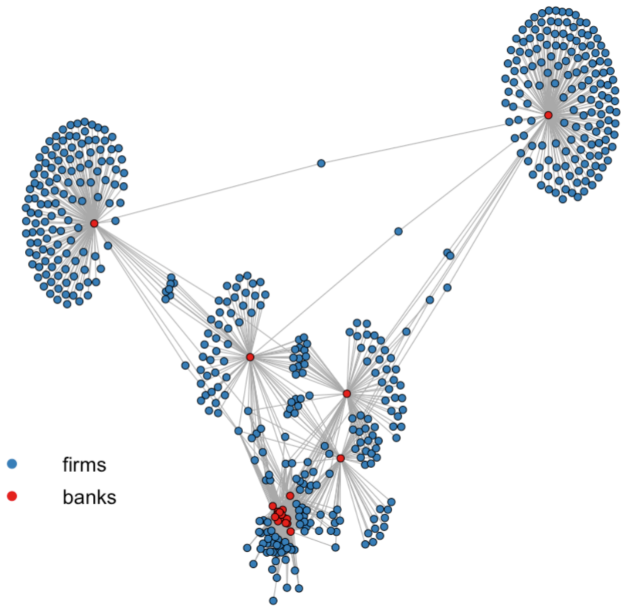

Figure 4: Credit network structure of a single baseline simulation run with 500 firms and 20 banks at time period $t = 400$.

Figure 4 captures the network structure within a single baseline simulation run at time $t = 400$. The figure shows that the credit links between banks and firms in the model build a network in which a few banks can provide a predominant part of the credit demand. The potential default of a bank with many credit links could destabilise the entire credit market in the event that the non-defaulting banks are unable to meet the remaining demand for credit. The network structure also shows that many firms have several credit links with different banks, which could destabilise all connected banks in the event of a firm's default.

In order to analyze the impact of credit-to-GDP-gap based CCyBs with a $\lambda = 400,000$ on the market structure within our model, we compare the market concentration and network density in the baseline scenario before and after the introduction of CCyBs in a total of

Table 3: Effects of introducing CCyBs on bank market structure λ

Parameter	baseline	$\lambda = 1,600$	$\lambda = 25,000$	$\lambda = 125,000$	$\lambda = 400,000$
Network density	13.576%	13.519%	13.455%	13.521%	13.642%
HHI (bank assets)	1261.934	1318.719	1375.806	1290.364	1242.918

Note: Means and standard deviations (in brackets) over 100 Monte Carlo Simulations.
*** p<0.01, ** p<0.05, * p<0.1.

100 Monte Carlo simulations. The network density indicates in percentage terms how many credit links exist out of the maximum number of possible credit linkages (Chinazzi et al. (2013)). The market concentration within the model simulation will be measured using the Hirshman-Herfindahl Index (HHI), which is the sum of the squared market shares of the banks (Jiménez et al. (2013)).

The simulation results show that the network density in the baseline scenario without CCyBs is 13.576% while the HHI is at 1261.934. Both variables are not significantly affected by the introduction of CCyBs, irrespective of the selected smoothing parameter within the CCyB calculation method. Thus, our model results do not show an impact of the macroprudential policy instrument of CCyBs on the market structure of the banking sector.

6 Concluding Remarks

The model proposed builds a network of heterogeneous firms and banks and a decentralized credit market where firms and banks interact directly with each other, based on the model of Riccetti et al. (2021). Based on this macro-financial agent-based model, this paper has examined the impact of the macroprudential policy instrument of CCyBs on financial stability and banking market structure and has examined the consequences that occur when the method of calculating CCyBs is changed. The original contribution of this work lies in the fact that we have implemented a mechanism of CCyBs and the compliance with minimum capital requirements into the model of Riccetti et al. (2021), which is closer to the recommendations by the BCBS according to Basel III. While Riccetti et al. (2021) consider credit growth rates for calculating CCyBs rates as suggested by Repullo and Saurina (2011), we have extended the model by introducing credit-to-GDP-gap based CCyBs which is in line with the Basel III requirements as well as examining the effects on financial stability and banking market structure due to a change in the smoothing parameter within the HP-filter for calculating CCyB rates.

The results of our analysis show, however, no significant impact of CCyBs on financial stability within our model. The same holds true for the variation of the smoothing parameter λ with respect to the calculation of the CCyB rate. The variation of λ also shows no significant impact on our macroeconomic variables of interest. One possible reason for this could be the level of the CCyB-rate. In this context, further analyses could shed light on whether the CCyB bandwidth range between $0 - 2.5\%$ is too low and thus does not have a noticeable effect on the macroeconomic level. The market structure in terms of market concentration and network density is also not significantly changed by the introduction of the CCyB within our model. Nevertheless, further research is needed in this area in particular, as the question of the impact of macroprudential regulation on market concentration and thus on financial stability has been largely ignored in academic research. In order to ensure that CCyBs are used as effectively as possible and to improve financial stability, CCyBs must be subject to ongoing evaluation of their impact on financial stability.

While

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