STAFF MEMO

Cyclical Capital Regulation and Dynamic Bank Behaviour

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Cyclical Capital Regulation and Dynamic Bank Behaviour[*]

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Abstract

In this paper we develop a dynamic model of bank behaviour to study cyclical capital regulation. We study the decision problem of a single bank that chooses its dividend policy and holds a portfolio of long-term loans (retail and corporate market), financed by internal (equity) and external (debt) funds. The demand for and return on bank lending is uncertain, determined by the state of the business cycle, which follows an exogenous Markov process. The model is calibrated using balance sheet and income statement data from seven of the largest Norwegian banking groups. To determine the probability and severity of a crisis we rely on cross-country data that covers several financial crises. In our main policy experiment we show that a time-varying capital requirement, which is decreased when loan losses are high, reduces the volatility of lending considerably compared with a fixed capital requirement. The reason for this is that lowering capital requirements when loan losses are high reduces the bank's need to cut lending, relative to a fixed requirement.

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1 Introduction

As from 2013, Norges Bank has issued advice on an additional capital requirement for banks: the countercyclical capital buffer (CCB).[1] The objective of the CCB is to strengthen banks' resilience to an impending downturn when financial imbalances are building up and counter excessive fluctuations in the credit supply that could amplify the economic cycle, see Norges Bank (2013). In the event of high loan losses that deplete banks' capital, a reduction in the buffer requirement can mitigate the procyclical effects of tighter bank lending.

In the data we observe that downturns are associated with contractions in banks' lending, but it is difficult to assess to what extent a fall in lending growth can be attributed to demand-side factors and to what extent banks' lending practices have a procyclical effect.

In this paper we develop a dynamic model of bank behaviour to help us understand the effects of cyclical capital regulation on banks' behaviour. Our structural model considers a single bank's dynamic optimization problem. The bank chooses a portfolio of long-term loans (to the retail and corporate market) and short-term securities, financed by internal (equity) and external (debt) funds. Bank loans are risky and both the demand for loans and the return depend on the state of the business cycle, which follows an exogenous Markov process. At each point in time, the bank has to satisfy a regulatory capital requirement. Capital moves slowly over time through retained earnings, whereas loans can be adjusted immediately, subject to a quadratic loan liquidation cost. If the bank does not find it optimal to operate as a bank, it liquidates its assets and exits the market facing limited liability.

The model allows for a rich implementation of a bank's optimization problem at the micro level. To embed this into a full macro structure allowing for feedback mechanisms between the bank and the rest of the economy is beyond the scope of this paper. Hence, given our partial equilibrium framework, our results are positive rather than normative.

We calibrate the model to be consistent with observed stylized facts of the Norwegian banking sector. Specifically, we use aggregated balance sheet and income statement data from seven of the largest Norwegian banking groups. By implementing estimated relationships for developments in non-performing loans and assuming a unit elasticity of demand with respect to the aggregate macro shock, the model replicates procyclical

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[1]In 2010, the CCB was introduced as a new policy tool for regulating banks (see Basel Committee on Banking Supervision (2010b)).

developments in bank lending. The probability and severity of the crisis scenario are estimated on international data and cover a wide range of financial crises. In the model, a sharp increase in the bank's loan losses erodes the bank's equity capital through negative profits. Furthermore, in line with the data, the bank's lending contracts, thus keeping the capital ratio above the regulatory requirement.

The paper has three main findings. First, if the capital requirement is fixed at a low level, the bank optimally holds a voluntary countercyclical buffer, but is subject to failure risk. Second, by introducing a sufficiently high fixed capital requirement, failure risk is essentially removed. However, the requirement induces higher volatility in bank lending. The bank does not find it optimal to hold a voluntary capital buffer above the regulatory requirement. As a result, the bank has to contract lending when its equity falls. Last, by introducing a time-varying capital requirement that varies around a sufficiently high fixed capital requirement, the overall volatility of bank lending is reduced compared with the fixed capital requirement regime.

We obtain these results by comparing three regimes of capital regulation. In the first exercise, we show that when the capital requirement is set to zero, the bank finds it optimal to self-insure against negative shocks by holding a capital buffer of 3.5% in normal times.[2] In the aftermath of a large negative shock (crisis times) that depletes equity, the capital ratio falls, the bank contracts lending (partly because loan demand falls, and partly in order to be resilient to future negative shocks), and exits the market if the shock is sufficiently severe. Hence, with a zero capital requirement, optimal bank behaviour induces both procyclical capital ratios and lending, and the risk of bank failure. In contrast, in the second exercise, we show that in a regime with a fixed capital requirement of 14.0%, the capital requirement is always close to binding. The bank responds to the higher capital requirement by accumulating capital and reducing lending in normal times. The bank now becomes more resilient to severe shocks and the exit probability conditional on a crisis is essentially zero. The exit probability is lower with a higher capital requirement because even after severe shocks, the bank's capital remains positive and the bank can tighten lending to fulfill the capital requirement. However, given a fixed and close to binding capital requirement, bank lending contracts more during severe downturns. Hence, lending becomes more procyclical. Since the bank does not accumulate a voluntary buffer above the requirement, implementing a time-varying

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[2]In the absence of risk, the bank would find it optimal to hold zero capital since in the calibrated model, capital is more costly than external debt (The Miller-Modigliani theorem does not therefore hold, see Modigliani and Miller (1958)). However, with risky loans, the bank faces the risk of failure, which implies permanent loss of bank charter value. Thus it optimally holds a buffer in order to self-insure.

requirement may dampen the regulatory-induced fluctuations in lending. Indeed, in the last exercise, we show that in a regime in which the capital requirement is 14.5% in normal times and 12.0% around crisis times, the volatility of lending is significantly reduced compared with a fixed capital requirement (corresponding to the long-run average capital requirement in the CCB regime).[3]

Our structural model setup draws heavily on the framework in Corbae and D'Erasmo (2014), who study the interaction between bank competition and regulation. Essentially, our model is a single bank version of their framework, extended to allow for multiple lending markets and long-term loans.[4] We also relate our model closely to the dynamic banking model in De Nicolo et al. (2014), who study capital regulation in a single-bank environment. However, they abstract from cyclical regulation.

Our findings are consistent with the work of Elizalde and Repullo (2007).[5] They explore a bank's incentives to hold a voluntary capital buffer and show that in a dynamic framework, variables such as the interest margin and the cost of capital are key determinants for a bank's economic capital (i.e. optimal capital level absent any regulatory requirements) and actual capital (optimal capital level with regulation).

In a closely related study, Repullo and Suarez (2013) develop a model in which bank equity is scarce in the aftermath of negative shocks to return on lending (i.e. slow-moving equity). They find that a risk-based capital regulation (à la Basel II), which involves higher requirements in times when bank loan losses are high, contributes to significantly more procyclical lending than a fixed requirement. This is consistent with our finding that setting higher requirements in times of low loan losses (normal times) induces less procyclical lending than a fixed requirement. However, Repullo and Suarez (2013) find that some regulatory-induced procyclicality of bank lending is optimal. The reason is that while raising capital requirements in times of high losses reduces lending, it also reduces bank failure probability. This channel is operative also in our calibrated model, but at current regulatory levels our big bank has essentially zero failure probability.

In a Norwegian context, Akram (2014) studies the effects of capital requirements in a macroeconometric framework and finds that capital requirements have significant effects on credit. In our model, a one percentage point increase in the capital requirement, from

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[3]The bank's adjustment under the two policy regimes illustrates the effects of a time-varying capital requirement, but the analysis does not indicate an appropriate level for the capital requirements.

[4]Related to this is also Corbae et al. (2016), who extend Corbae and D'Erasmo (2014) along similar dimensions to perform bank stress testing.

[5]In contrast to Elizalde and Repullo (2007) we consider slow moving capital (through retained earnings). This is important when considering a dynamic capital requirement, since if the bank can fully recapitalize in the aftermath of negative shocks, there would be no role for dynamic regulation.

a benchmark of 14%, reduces our bank's lending by 2.1%. This is higher than what Akram (2014) finds (0.71%), but within the range of international evidence reported in Basel Committee on Banking Supervision (2010c).[6]

The paper proceeds as follows. In the next section we document some key stylized facts about the Norwegian banking industry, exploiting a newly constructed panel dataset, see Appendix A. In Section 3 we present the model, which is calibrated in Section 4. The calibrated model is used for policy analysis in Section 5. The last section summarizes.

2 The cyclical behaviour of Norwegian banks

This section documents the cyclical behaviour of Norwegian banks over the business cycle. In our model framework, the state of the business cycle follows an exogenous Markov process. We calibrate the model to be consistent with observed stylized facts from the Norwegian banking sector. Specifically, we study the standard deviation of the cyclical component of key banking variables and the correlation of these indicators with detrended GDP.

Our findings are generally in line with Corbae and D'Erasmo (2013).[7] The results indicate that both bank lending and funding are procyclical with respect to the output gap, whereas banks' non-performing loans are strongly countercyclical. We find that bank equity is accumulated in periods of rising economic activity. When activity drops, non-performing loans spike and equity falls. However, in the sample period, banks' lending also contracts during recessions, leaving the cyclical component of banks' equity ratio close to uncorrelated with the output gap.[8] The data thus indicates that Norwegian banks look through the business cycle when adjusting their equity ratio. In Appendix B we explore the properties of the bank indicators over the financial cycle (lasting 10-20 years) and find that Norwegian banks tend to decrease equity relative to total assets in

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[6] In contrast, Vale (2011) finds in a Norwegian context that a sizeable increase in banks' equity ratio, from 5.5% to 11% will only result in a reduction in Norwegians banks' lending in the range of 0.33% to 1.23%.

[7] Corbae and D'Erasmo (2013) documents banking facts for the U.S. using data from the Consolidated Report of Condition and Income that insured banks submit to the Federal Reserve each quarter. They find that loans and deposits are procyclical with respect to detrended GDP and that banks' delinquency rate is countercyclical (the delinquency rate is the ratio of loans past due 90 days or more plus non-accrual loans divided by total loans). Corbae and D'Erasmo (2014) document the correlation of banks' Tier 1 capital ratio with detrended GDP according to bank size. They find that large banks have a countercyclical capital ratio, whereas the correlation is less countercyclical for small banks.

[8] The equity ratio is here defined as equity relative to total assets.

long periods of credit booms.

2.1 Measuring banks' balance sheet and income

We document the cyclical behaviour of key variables for banks such as lending to customers, problem loans (i.e. reported non-performing loans and other loans with a high probability of default), equity ratio, customer deposits and wholesale funding. Banks' wholesale funding is defined as total liabilities less customer deposits and equity. Even though in the model we focus on one source of external funding (see Section 3), we choose to document the cyclical properties of different sources of funding.

The increased complexity of the banking sector and the lack of historically consolidated data have made it necessary to collect data from several sources. The data has been collected from three main sources: Banks and financial undertakings' financial reporting to Norwegian authorities ("Offentlig regnskapsrapportering for banker og finansieringsforetak (ORBOF)"), SNL Financial and OECD banking statistics. We use the constructed data set described in Appendix A and aggregate the balance sheet of all Norwegian banks, taking into account their exposures in fully owned mortgage companies and the largest jointly owned covered bond mortgage companies.[9] When analyzing developments in lending and problem loans, we include all mortgage companies. For some measures, such as banks' equity, wholesale funding and customer deposits, we exclude foreign branches. All balance sheet indicators are break-adjusted for the inclusion of mortgage companies into the ORBOF database in 1996Q1. All balance sheet components are measured in real terms.[10]

When analyzing developments in banks' loans and problem loans, we follow Dahl and Vatne (2012) and distinguish between the retail and corporate market.[11] This distinction is in line with the breakdown in banks' annual reports.

2.2 Calculating the cyclical components

To study the cyclical properties of the data, we apply the Hodrick-Prescott (HP) filter, see Hodrick and Prescott (1997). The method separates a time series into a cyclical and a trend component, and the smoothness of the trend is determined by the parameter

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[9]Some smaller banks and mortgage companies with limited time series are excluded from the sample.

[10]We deflate by the consumer price index adjusted for taxes and excluding energy prices.

[11]The retail market comprises wage earners and benefit recipients. The corporate market comprises private non-financial incorporated and unincorporated enterprises, private non-profit institutions serving enterprises, unincorporated enterprises within households and housing cooperatives etc.

λ.[12] The higher the value of λ, the higher is the degree of smoothing of the trend.

We report the correlation between the cyclical components of banks' balance sheets and the business cycle. For the business cycle (horizon of about 2-8 years) we consider HP filters with λ equal to 1600, 6400 and 10 000.[13] As an indicator of the business cycle we apply the deviation of the log of GDP for mainland Norway from trend (here defined as the output gap).

2.3 Volatility

Table 1 reports the standard deviation (volatility) of the cyclical component of GDP for mainland Norway and the balance sheet indicators. In addition, we report the ratio of the standard deviation of each balance sheet component to the standard deviation of the output gap.

The standard deviation of the cyclical component of GDP is in the range 1.5-2.1 depending on the value of the smoothing parameter. These estimates are at the higher end of the range of estimates reported by Husebø and Wilhelmsen (2005) for the period 1982-2001. Their sample ends just before a period of financial vulnerability in 2002-2003 and also excludes the financial crisis in the period 2008Q3-2009Q3.

Table 1 shows that banks' balance sheet components are generally more volatile than GDP. The cyclical components of banks' lending are 2.6-3.3 times more volatile than the cyclical component of GDP for mainland Norway. In the period 1992-2015, volatility is mainly driven by loans to the corporate sector. Next, we notice that the cyclical component of banks' real problem loans is clearly the most volatile item on the balance sheet. Real problem loans are 13.1-13.6 times more volatile than GDP in the period 1992-2015. Also for this variable, the corporate sector is more volatile than the retail sector. On the liability side, wholesale funding is the most volatile component. In the period 1980-2015, banks' wholesale funding was 6.5-8.0 times as volatile as GDP for mainland Norway.

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[12]We apply a two-sided HP filter for all trend estimations. All cyclical components of levels are calculated as the deviation of the log of the variable from the trend. All cyclical components of ratios are calculated as the percentage point deviation of the variable from the trend. All the time series are seasonally adjusted using a X12-ARIMA before we apply the HP filter. Mathematically, the HP filter finds the trend series μ_t, which minimizes the following sum for a given value of λ: $\sum_{t=1}^{T}(y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T-1}[(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2$.

[13]Using quarterly time series for the US economy, Kydland and Prescott (1990) suggest that a value of λ equal to 1600 is reasonable to capture business cycles when using the HP filter. Husebø and Wilhelmsen (2005) find that a λ smaller than 1600 results in unreasonably volatile trend values as Norwegian macroeconomic data are more volatile than US and euro area data.

Table 1: Standard deviations of the cyclical components[1] of mainland GDP and banks' balance sheet components

Indicator (I)	1980Q1-2015Q4		1992Q1 -2015Q4	
	std(I)	std(I)/std(GDP)	std(I)	std(I)/std(GDP)
GDP, mainland Norway	1.5-2.1	1	1.3-1.8	1
Real lending	3.9-6.9	2.6-3.3	3.9-5.0	2.6-3.0
- retail			1.9-3.0	1.4-1.7
- corporate			4.5-6.9	3.4-3.8
Real problem loans			17.7-23.7	13.1-13.6
- retail			9.7-13.5	7.4-7.5
- corporate			22.8-29.8	16.6-17.5
Problem loan ratio[2] (p.p. dev.)			0.4-0.7	
- retail (p.p. dev.)			0.2-0.3	
- corporate (p.p. dev.)			0.8-1.1	
Real bank equity[3]	8.0-10.8	5.1-5.4	5.6-8.1	4.3-4.5
Real total assets[3]	4.4-7.0	3.0-3.3	3.8-5.7	3.0-3.1
Equity ratio[3] (p.p. dev.)	0.4-0.5		0.4-0.5	
Real customer deposits[3]	3.2-3.9	1.9-2.1	3.1-3.8	2.1-2.4
Real wholesale funding[3]	9.7-16.8	6.5-8.0	8.3-14.0	6.4-7.8

1) Detrended using the HP filter with different smoothing parameters (1600, 6400 and 10 000). Detrended the log of the variables.
2) Problem loans in percent of lending to the sector.
3) Excluding foreign branches.
Sources: OECD, SNL Financial, Statistics Norway, and Norges Bank

As expected, the volatility of banks' real equity drops if we exclude the banking crisis in the period 1988Q2-1993Q3, see Table 1.

2.4 Cross-correlations

This section documents the correlation between each bank balance sheet indicator and the output gap. For the sake of brevity, only the results with $\lambda = 6400$ are reported. In Table 2, a positive correlation coefficient indicates procyclical behaviour of the series, whereas a negative correlation indicates a countercyclical series. In addition to the contemporaneous correlation coefficient, the table shows the absolute max lead or lag coefficient and the corresponding quarter in parenthesis with lead (+) and lag (-). A maximum coefficient at t=-2 means that the series tends to lag the business cycle by two quarters.

Table 2: Cross-correlations with lag(-) and lead(+) with respect to detrended log GDP. Detrended using the HP filter, lambda = 6400
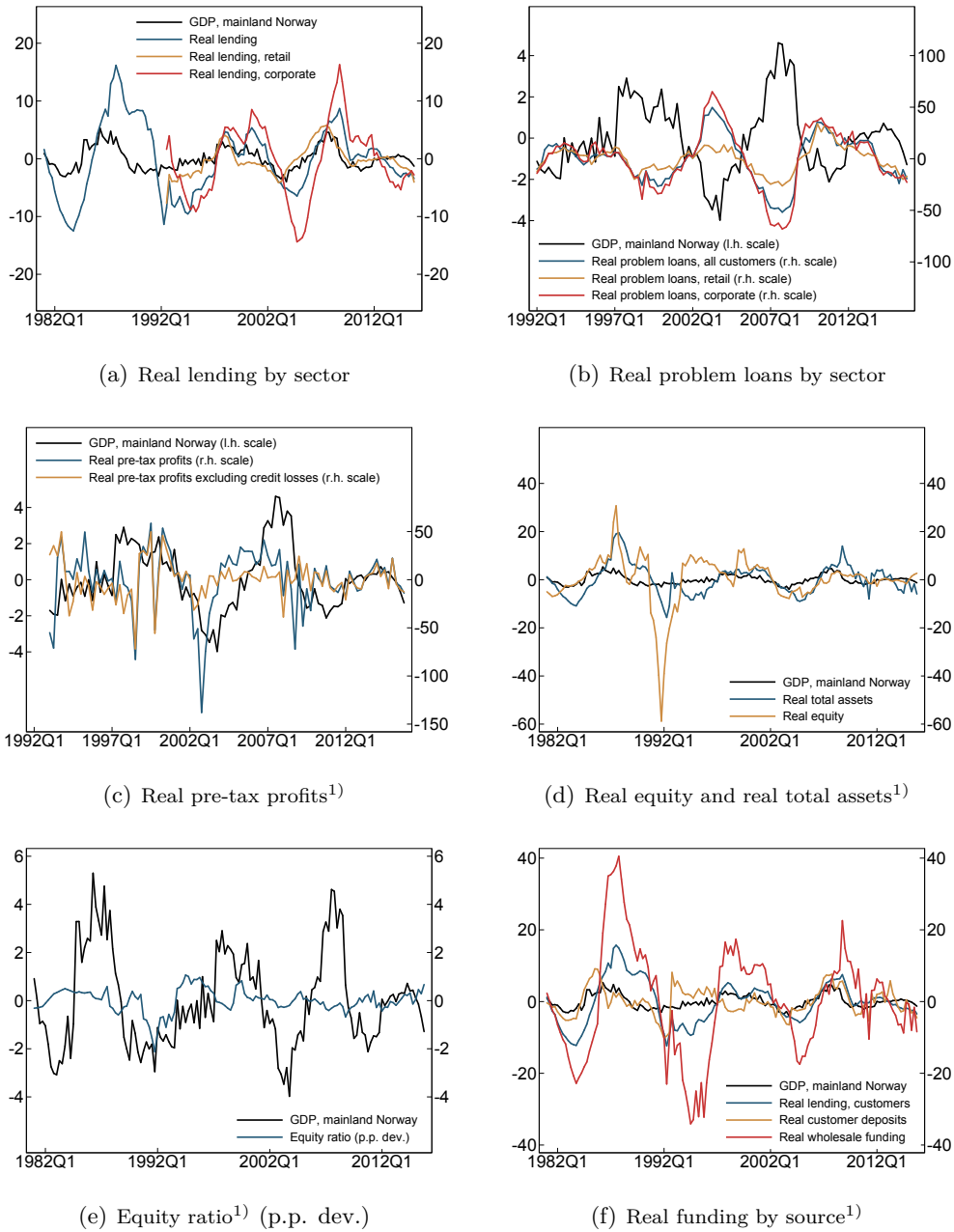
	1980Q1 - 2015Q4		1992Q1 - 2015Q4	
	t = 0	max corr.	t = 0	max corr.
Real lending	0.53	0.70	0.64	0.73
		(-4)		(-3)
- retail			0.74	0.76
				(2)
- corporate			0.38	0.77
				(-5)
Real problem loans			-0.83	-0.83
				(0)
- retail			-0.67	-0.70
				(-1)
- corporate			-0.84	-0.84
				(0)
Problem loan ratio[1] (p.p. dev.)			-0.74	-0.74
				(0)
- retail[1]			-0.66	-0.70
				(-1)
- corporate[1]			-0.77	-0.78
				(-1)
Real bank equity[2]	0.43	0.44	0.34	0.40
		(-4)		(-3)
Real total assets[2]	0.54	0.75	0.51	0.72
		(-5)		(-4)
Equity ratio[2] (p.p. dev.)	0.11	0.37	0.01	0.28
		(9)		(7)
Real customer deposits[2]	0.55	0.56	0.44	0.45
		(2)		(2)
Real wholesale funding[2]	0.44	0.72	0.39	0.63
		(-5)		(-5)

1) Problem loans in percent of lending to the sector.
2) Excluding foreign branches.
Sources: OECD, SNL Financial, Statistics Norway and Norges Bank

Figure 1: The cyclical components of bank indicators and GDP for mainland Norway

(a) Real lending by sector

(b) Real problem loans by sector

(c) Real pre-tax profits[1]

(d) Real equity and real total assets[1]

(e) Equity ratio[1] (p.p. dev.)

(f) Real funding by source[1]

Deviation of the log of the variable from estimated trends. The trend is estimated using a two-sided HP filter with lambda=6400. The sample period is 1980Q1-2015Q4 for lending to customers, equity, total assets, customer deposits and wholesale funding. The sample period is 1992Q1-2015Q4 for lending by sector and problem loans. The sample period is 1993Q1-2015Q4 for pre-tax profits.
1) Excluding foreign branches.
Sources: OECD, SNL Financial, Statistics Norway and Norges Bank

Bank loans

Loans to customers are Norwegian banks' main asset. Figure 1a illustrates the pro-cyclicality of bank lending. The cross-correlations reported in Table 2 suggest that the cyclical component of real lending lags the business cycle by 3-4 quarters. Norwegian banks clearly adjust their lending over the cycle, expanding lending during booms and contracting it during recessions. However, there are differences in both lending volatility and lag structure between the corporate and retail market. Lending in the retail market tends to lead the business cycle by 2 quarters, whereas credit in the corporate market lags the cycle by 5 quarters and is considerably more volatile.

Problem loans reflect the volume of outstanding loans to banks' customers that are at risk of defaulting.[14] According to Table 2 and Figure 1b, problem loans are highly countercyclical and move contemporaneously with the business cycle. A slowdown in activity is associated with an increase in problem loans. Figure 1c shows the importance of banks' credit losses in determining procyclical developments in banks' pre-tax profits in the sample period.

In line with bank lending to the corporate market, problem loans in the corporate market have a much higher volatility than problem loans in the retail market, see Table 1. In Norway, the cost of personal bankruptcy is high as households are liable for a large share of the amount borrowed. Experience from previous crises, both in Norway and internationally, suggests that households rarely default on their loans, see Kragh-Sørensen and Solheim (2014).[15] However, large drops in activity may cause significant adjustments in saving and consumption that can amplify a drop in the profitability and solvency of enterprises.

Bank equity ratio

Equity is banks' primary loss-absorbing buffer and is one of many measures of banks' financial strength. The cyclical component of banks' real equity has a positive correlation with our business cycle indicator, see Table 2 and Figure 1d. The data suggests that Norwegian banks tend to increase real equity during business cycle booms in line with asset expansions. In business cycle busts, activity declines and banks' losses increase.

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[14]We focus on problem loans since, in contrast to banks' recorded loan losses, longer time series on banks' problem loans can be separated into the retail and corporate sector. There is a close connection between banks' problem loans and recorded losses, see discussion in Berge and Boye (2007).

[15]A clear exception is the financial crisis in 2008 where US banks experienced a large-scale increase in actual losses on household loans, see Kragh-Sørensen and Solheim (2014).

High losses can erode banks' equity through negative profits. During the Norwegian banking crisis, as loan losses spiked, banks' real equity contracted sharply. However, in all periods where equity falls, banks' assets also contract. It follows that the short-term cyclical component of banks' equity ratio is close to acyclical, see Figure 1e and Table 2.

Bank funding

Banks' real customer deposits and real wholesale funding are procyclical, see Table 2 and Figure 1f. However, there is a considerable difference in volatility and lag structure between the two liability components, see Table 1 and Table 2. The cyclical component of banks' real customer deposits tends to lead the business cycle by 2 quarters, whereas real wholesale funding lags the business cycle by approximately 1 year. Interestingly, we notice from Figure 1f that in the years where real customer deposits do not track banks' real lending, the movement in real wholesale funding is strong. Hahm et al. (2013) propose that as retail deposits have a tendency to grow in line with the size of the economy and the size of household wealth, banks turn to other sources of funding during lending booms to support their credit growth. Figure 1f suggests that the same behaviour could be present amongst Norwegian banks during periods of high credit growth.

3 The economic environment

This section lays out the economic environment. The model is based on Corbae and D'Erasmo (2014), and closely related to De Nicolo et al. (2014) and Elizalde and Repullo (2007).

Time is discrete and infinite ($t = 0, 1, 2...$). In a partial equilibrium setting a single bank with market power maximizes the discounted value of future dividends by optimizing over a portfolio of long-term loans and short-term securities, financed by internal (equity) and external (debt) funds. At the beginning of each period t, the bank chooses how many loans to sector s to extend (L_{st}) and how many securities (A_t) to hold. The amount of external funding (d) is given exogenously, and equity (e_t) is predetermined. When choosing loan supply, the bank takes into account that higher supply leads to a lower interest rate (r_{st}^L). At the end of the period, profits are realized. Bank loans are risky and the bank faces uncertainty about the fraction of defaulting loans ($1 - p_{st}$). After profits are realized, the bank chooses whether to exit or stay in the market by comparing its charter value with the liquidation value of its balance sheet. Due to the presence of fixed operating costs, the model features non-trivial exit decisions at strictly

positive equity levels. If the bank exits, it liquidates its assets and pays back creditors, facing limited liability. The bank's external funding cost r^d is independent of the bank's likelihood of bankruptcy, hence creditors do not take into account the bank's failure risk.[16] If the bank stays, it chooses how much to pay out as dividends and how much to retain as equity for period $t+1$. A key friction in the model is that new equity issuance is prohibitively costly. Equity thus moves slowly over time, through retained earnings. Another key friction is that bank shareholders discount future dividends at a higher rate than the safe return on securities, implying that absent any risk of failure, the bank would prefer debt over equity.

We want to study how capital regulation affects bank behaviour. Regulation is implemented by requiring the bank to hold a level of equity at least as large as a fraction φ of the risk-weighted value of its assets. The requirement is implemented as a hard constraint, implying that violation of the requirement induces liquidation of the bank.

3.1 Model

The bank's objective is to maximize the expected discounted stream of dividends:

$$\mathbb{E}_t \sum_{i=t+1}^{\infty} \beta^{i-t} \mathcal{D}_i. \tag{1}$$

Each period t is divided into two sub-periods. At the beginning of the period, before any choices are made, the bank's balance sheet is given by:

$$e_t = a_t + \sum_S \ell_{st} - d, \tag{2}$$

which states that equity e_t equals net wealth, which consist of securities a_t and loan stocks ℓ_{st} carried over from the previous period net of debt d.

The bank then chooses how much to invest in period t loans and securities (L_{st}, A_t) subject to the resource constraint:

$$a_t - A_t = \sum_s \left[(L_{st} - \ell_{st}) + \Psi(L_{st}, \ell_{st}) \right], \tag{3}$$

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[16]In the model there is only one type of bank debt, whereas in the data bank debt consists of both insured/secured and unsecured debt. Our model assumption that r^d is independent of the bank's probability of bankruptcy is consistent with data to the extent that unsecured creditors believe that the bank is too big to fail.

and regulatory capital requirement:

$$\varphi(z_t)H(\{L_s\}_{\mathcal{S}}, A_t) \leq e_t, \tag{4}$$

where $\varphi(z_t)$ is the (possibly) time-varying risk-weighted requirement and $H(L, A)$ denotes the function mapping assets to risk-weighted assets. Whenever loan growth is negative, the bank pays an adjustment cost:

$$\Psi_s(L_{st}, \ell_{st}) = \mathbb{I}(L_{st} < \ell_{st})\psi_s[L_s - \ell_{st}]^2 \, , \forall s \in \mathcal{S}. \tag{5}$$

The bank faces one source of uncertainty. Loan demand and default frequency are subject to the macro shock z. The end of the period is initiated with the realization of this shock. The new aggregate state z_{t+1} determines the share of performing loans as well as the period $t + 1$ loan demand.

We assume that the bank under consideration sets its loan supply taking into account a reduced form response by other credit suppliers. Let the loan supply of other credit suppliers be given by $L^o_{st} = M_s(z_t, L_{st})$, where M_s denotes the reduced form response function. The loan interest rate is determined by aggregate loan supply $L^A_{st} = L^o_{st} + L_{st}$ and the state of the economy, through the inverse demand function:

$$r^L_{st} = f_s^{-1}(L^A_{st}, z_t), \tag{6}$$

which is downward sloping in aggregate loan supply and upward sloping in the state of the economy z. The performing loans share is given by:

$$p_{st} = P_s(r^L_{st}, z_t, z_{t+1}), \tag{7}$$

which depends on the loan rate, and the state of the macro shock.

Loans mature at an exogenous rate m_s each period and a fraction $(1 - p_{st})$ of the loan portfolio is in default. Given the beginning-of-period choices and the shock realizations, the end-of-period cash flow is given by:

$$C_t = \sum_{\mathcal{S}} [p_{st}(m_s + r^L_{st}) - c_s]L_{st} + r^a A_t - r^d d - \kappa, \tag{8}$$

where the first term captures cash flow from performing loans net of proportional lending cost c_s, and (r^a, r^d) interest rate on securities and debt, and κ the fixed cost. The bank

now decides on its dividend policy, $\mathcal{D}_t$. The cash flow is distributed to equity holders or retained. Moreover, the bank has access to a short-term liquidity market in which they can borrow liquidity at cost r^b. Let $B_t < 0$ denote retained earnings and $B_t > 0$ denote short–run borrowing. Then, dividends are determined as:

$$\mathcal{D}_t = C_t + B_t - tax_t, \tag{9}$$

where tax_t denotes the tax payment. The bank pays a 27% tax on positive profits where profits are defined as:

$$\pi_t = \sum_S \left[\left(p_{st} r_{st}^L - (1 - p_{st}) \lambda_s(z_{t+1}) - c_s \right) L_{st} - \Psi_s(L_{st}, \ell_{st}) \right] + r^a A_t - r^d d - \kappa - r^b B_t, \tag{10}$$

where $\lambda_s(z_{t+1})$ denotes loss given default, which depends on the state z_{t+1}, and r^b the cost of short-term borrowing.

The bank is constrained in its dividend policy by $\mathcal{D}_t \geq 0$, which is equivalent to ruling out new equity issuance, as dividends are constrained below at zero. If the bank wants to stay in the market despite contemporaneous negative cash flow, it has to access the short–term liquidity market ($B_t > 0$) so as not to violate the non-negativity constraint on dividends. In contrast, if cash flow is positive, the bank may not want to pay everything out as dividends but instead retain earnings ($B_t < 0$) to raise next period's initial securities a_{t+1} as shown below. Short–term borrowing requires collateral in the form of securities:

$$(1 + r^b) B_t \leq A_t, \tag{11}$$

with $r^b = 0$ if $B_t \leq 0$. Constraint (11) also reflects the assumption that loans on the balance sheet cannot be used as collateral for short-term borrowing.

Each period, a fraction m_s of loans exogenously matures and non-performing loans are written down by a fraction $\lambda_s(z_{t+1})$. Therefore, beginning-of-period $t + 1$ heritage loans are given by:

$$\ell_{st+1} = [1 - m_s] p_{st} L_{st} + (1 - p_{st})(1 - \lambda_s(z_{t+1})) L_{st}, \forall s \in \mathcal{S} \tag{12}$$

Also, at the beginning of period $t+1$, before any choice is made, the short–term liquidity market clears, i.e. B_{t+1} is repaid. Thus, beginning-of-next-period securities a_{t+1} is given

by:

$$a_{t+1} = A_t - (1 + r^b)B_t \geq 0. \tag{13}$$

As discussed above, retained earnings ($B_t < 0$) raise a_{t+1} and thus net wealth at the beginning of the next period, which can be invested in either loans or securities.

The bank may choose to exit the market end-of-period, in which case assets are liquidated and creditors repaid. Note that the bank has to pay liquidation cost on its loan stock. Since the bank faces limited liability, the value of exit is thus given by:

$$\max\left\{ 0, \sum_{\mathcal{S}}((m_s + r_{st}^L)p_{st} - c_s)L_{st} + \ell_{st+1} - \Psi_s(0, \ell_{st+1}) + (1 + r^a)A_t - (1 + r^d)d - \kappa \right\}. \tag{14}$$

Figure 2 summarizes the timing.

Figure 2: Timing
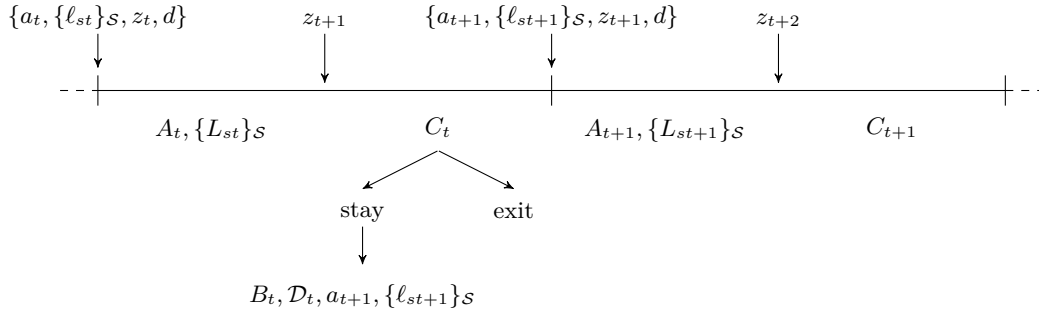
3.2 Bank's dynamic programming problem

Due to the recursive nature of the bank's problem, we can drop time subscripts. The value of the bank at the beginning of the period is given by:

$$V(a, \{\ell_s\}_{\mathcal{S}}, z, d) = \max_{A, \{L_s\}_{\mathcal{S}}} \beta \, \mathbb{E}_{z'|z} W(A, \{L_s\}_{\mathcal{S}}, z', d) \ \ s.t.$$

$$e = a + \sum_{\mathcal{S}} \ell_s - d$$

$$a - A = \sum_s [(L_s - \ell_s) + \Psi(L_s, \ell_s)] \tag{15}$$

$$\varphi(z)H(\{L_s\}_{\mathcal{S}}, A) \leq e$$

$$r_s^L = f_s^{-1}(L_s^A, z) \, , \forall s \in \mathcal{S}.$$

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The end-of-period value is given by:

$$W\left(A, \{L_s\}_\mathcal{S}, z', d\right) = \max_{x \in \{0,1\}} \left\{ W^{x=0}(A, \{L_s\}_\mathcal{S}, z', d), W^{x=1}(A, \{L_s\}_\mathcal{S}, z', d) \right\}, \quad (16)$$

with exit value $W^{x=1}$ given by equation 14. The continuation value is given by:

$$
\begin{aligned}
W^{x=0}(A, \{L_s\}_\mathcal{S}, z', d) &= \max_{B \leq \frac{A}{1+r^b}} \left\{ \mathcal{D} + V(a', \{\ell'_s\}_\mathcal{S}, z', d) \right\} \quad s.t. \\
C &= \sum_\mathcal{S} [p_s(m_s + r_s^L) - c_s]L_s + r^a A - r^d d - \kappa \\
\mathcal{D} &= C + B - tax \\
a' &= A - (1 + r^b)B \geq 0 \\
\ell'_s &= [1 - m_s]p_s L_s + (1 - p_s)[1 - \lambda_s(z')]L_s, \quad \forall s \in \mathcal{S}.
\end{aligned}
\quad (17)
$$

4   Calibration

The model period is set to one year. The parametrization is based on a combination of external and internal calibration. To calibrate the parameters reflecting the bank's earning and balance sheet position, we exploit the constructed micro dataset on banks' balance sheets and income statements described in Appendix A. The calibrated capital requirement is based on current regulations for banks' Common Equity Tier (CET1) capital ratio. The bank's risk-weighted assets are based on the average reported risk weights of banks taking advantage of the internal ratings-based approach (IRB banks). In addition, we take into account the Basel I transitional floor. In Section 2 we show that both lending and non-performing loans in the corporate sector are considerably more volatile than in the retail sector. Thus, to capture the heterogeneity of banks' customers, we allow for two sectors in the model, $s \in \mathcal{S} = \{ret, C\&I\}$, where ret denotes the retail sector and $C\&I$ denotes the corporate sector. To determine the probability and severity of a crisis, we rely on cross-country data that covers several financial crises, see Anundsen et al. (2016) and Laeven and Valencia (2012).

In the model, we consider the dynamic decision problem of a single big bank. In the data, we assume our big bank to be the asset-weighted average of the seven largest Norwegian banking groups (as of 2015Q4). We identify the largest Norwegian banks

according to total lending to the Norwegian corporate and retail sector.[17] In the constructed data set described in Appendix A, these seven banks have a market share of about 60% of lending by banks and mortgage companies to the Norwegian corporate sector and to the retail sector.[18] Furthermore, the group consists of six IRB banks and one smaller bank that uses the standardized approach. The group also covers two out of the three systemically important banks in Norway.[19] In Appendix C, we illustrate the variation in the composition of banks' balance sheets according to bank size. We note that the seven largest banks have on average a lower equity to total asset ratio and historically a higher exposure rate to the corporate sector than most of the other banks. To avoid shifts in the series due to mergers, we aggregate historical data to include all banking institutions that are part of the top seven banks in 2015Q4. All values are reported in real terms. We deflate using the consumer price index adjusted for taxes and excluding energy prices.

4.1 Aggregate shock

We begin the calibration by estimating the stochastic process for the aggregate macro shock z_t. The aggregate shock z_t is assumed to fluctuate between three states, $z_t \in \{z_g, z_b, z_c\}$, which we refer to as the good, the bad and the crisis state, respectively, measured by GDP for mainland Norway. The good and bad states reflect normal business cycles, with respective booms and busts. The crisis state captures the more rare event of a severe banking crisis with a significant decline in activity and a sharp increase in non-performing loans.

Let p_{ij} denote the probability of switching from state i to state j. The transition matrix is given by:

$$F(z', z) = \begin{bmatrix} p_{gg} & p_{gb} & p_{gc} \\ p_{bg} & p_{bb} & p_{bc} \\ p_{cg} & p_{cb} & p_{cc} \end{bmatrix} \tag{18}$$

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[17]The identified seven largest banks are: DNB Bank, Nordea Bank Norge, SpareBank 1 SR-Bank, Sparebanken Vest, SpareBank 1 SMN, SpareBank 1 Nord-Norge and Sparebanken Sør.

[18]In the constructed dataset, six out of the seven banks are covered by the SNL Financial in the period 2008-2015.

[19]The Ministry of Finance has issued the Regulation on the designation of systemically important financial institutions and designated DNB ASA , Nordea Bank Norge ASA and Kommunalbanken AS as systemically important. Designations will be reviewed annually. Institutions with total assets of at least 10% of mainland GDP, or a share of the lending market of at least 5%, will, as a main rule, be designated as systemically important.

Table 3: Calibration of aggregated shock

Parameter/state description	Parameter/state	Values
Aggregate shock	z_g, z_b, z_c	1 0.975 0.96
Transition probabilities from good state	p_{gg}, p_{gb}, p_{gc}	0.75 0.21 0.04
Transition probabilities from bad state	p_{bg}, p_{bb}, p_{bc}	0.21 0.75 0.04
Transition probabilities from crisis state	p_{cg}, p_{cb}, p_{cc}	0 0.29 0.71

Sources: Statistics Norway and Norges Bank.

Table 3 reports all annual transition probabilities and normalized state values.[20] The estimation of the z_t process is done in two steps, where we separately estimate the crisis state and normal time fluctuations.

First, regarding the crisis state we use a quarterly panel dataset for 20 OECD countries in the period 1975Q1-2014Q2 to determine the transition in and out of a crisis. The identified financial crises are the same as in Anundsen et al. (2016) and relies on Laeven and Valencia (2008, 2010, 2012), Reinhart and Rogoff (2008, 2009a,b) and Babecky et al. (2014). The probability of entering a crisis is based on the frequency of crisis starts in the data. We identify 32 crises starts from a total of 3160 quarters, where 405 quarters are crisis observations and 2755 quarters are normal times observations.[21] Based on the frequency of entering a crisis from normal times, we find a conditional quarterly probability of 1.1%. We set the annual probability, $p_{gc} = p_{bc} = 0.04$, which is somewhat lower than the probability associated with our dataset, but in line with other findings in the literature, see e.g. Bordo et al. (2001) and Schularick and Taylor (2012). Further, we normalize the good state to unity and set $z_c = 0.96$ to match the decline from our good state to crisis trough. This is line with the findings of Anundsen et al. (2016), who based on 33 financial crisis episodes find a decline in the output gap from peak to trough of 4 percentage points. The probability of recovery from crisis is based on the observed duration of a crisis. We observe 33 quarters of recovery from crisis, which gives a conditional annual probability of crisis recovery of 29%. We assume that recovery from crisis always occurs through the bad state, hence $p_{cb} = 0.29$.

Next, we consider the process for normal business cycle fluctuations (z_g, z_b). Based on an estimated AR(1)-process on the output gap in the period 1978Q1-2015Q4, we determine the discrete transition probabilities following the method proposed by Tauchen

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[20]The parameters are estimated on quarterly data. We transform the quarterly transition probabilities to annual probabilities by $p_{ii} = (p_{ii}^Q)^4$ where $i = g, b, c$. The annual probability of entering a crisis is set by $p_{ic} = 1 - (1 - (p_{ic}^Q))^4$ where $i = g, b$.

[21]If the end of the crisis is not specified, we assume a crisis duration of eight quarters.

and Hussey (1991).[22] The annual transition probabilities are estimated to $p_{gb} = p_{bg} = 0.21$. It follows that the probability of remaining in either the good or bad state is $p_{bb} = p_{gg} = 0.75$.[23] The contraction from average business cycle boom to average business cycle bust is estimated at 2.54 percentage points and hence we set $z_b = 0.9746$ to match the average contraction.

4.2 External calibration of bank-specific parameters

A subset of the bank-specific parameters (r^a, r^d, r^b, c_s) is taken directly from corresponding long-run averages observed in the data, see Table 4 . The interest rate (r^a) on banks' securities is determined by net profit and losses on financial instruments, interest income on bonds and certificates and other interest income. Net income is measured relative to the banks' financial instruments and fixed assets.

The interest rate on banks' funding (r^d) is determined by the interest charged on banks' deposits from customers and wholesale funding such as issued certificates and bonds. As part of the crisis scenario, we assume that when $z_t = z_c$, the cost of funding is raised to the level of the interest rate on securities.

For the unit cost of lending, we assume $c_{ret} = c_{C\&I} = c$. In the data, we measure this as total net non-interest expenses, determined by the banks' personnel expenses, IT costs and net provision income on loans over total lending to customers.

Finally, the interest rate on short-term liquidity (r^b) is based on a financial macro indicator: three-month NIBOR (Norwegian Inter Bank offered Rate).

4.2.1 Calibration of banks' defaulting loans

Let the event of crisis impact be denoted as $Z_I = \{z_t \in (z_g, z_b) \quad \& \quad z_{t+1} = z_c\}$. The default relation is given by:

$$P_s(r_{st}, z_t, z_{t+1}) = \begin{cases} P^s_{impact} & , (z_t, z_{t+1}) \in Z_I \\ \eta^s_0 + \eta^s_1 z_{t+1} + \eta^s_2 r_{st} & , (z_t, z_{t+1}) \notin Z_I. \end{cases} \tag{19}$$

At crisis impact, new problem loans are assumed to rise considerably, reflecting the

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[22]The output gap is calculated as the deviation of the log of GDP for mainland Norway from a two-sided HP trend using a smoothing parameter of $\lambda = 6400$.

[23]The transition probabilities capturing normal business cycle fluctuations are estimated at $p^N_{gb} = p^N_{bg} = 0.22$ and $p^N_{bb} = p^N_{gg} = 0.78$. We scale the transition probabilities capturing normal business fluctuations proportionally, taking account of the annual 4% probability of entering a crisis from either the good or bad state.

Table 4: External calibration of bank-specific parameters

Parameter description	Parameter	Value
Real funding rate[1]	r^d	1.84
Real interest rate on securities[1]	r^a	1.98
Non-interest expenses[1]	c	0.52
Real short term rate	r^b	1.76
Loss given default - good and bad state	$\lambda_{g,b}$	10
Loss given default - crises state	λ_c	30
Risk weight - retail exposures, IRB approach[2]	$\omega^{IRB,ret}$	21
Risk weight - corporate exposures, IRB approach[2]	$\omega^{IRB,C\&I}$	84
Risk weight - retail exposures, Basel I[3]	$\omega^{BI,ret}$	50
Risk weight - corporate exposures, Basel I[3]	$\omega^{BI,C\&I}$	100
Risk weight - market risk[4]	ω^A	3
Risk weight - operational risk and other credit exposures[5]	ω	7

1) The sample period is 2001Q1-2015Q4. The sample average is based on the weighted average of the top seven banks. Values correspond to annual rates.
2) Risk weights are based on the average reported risk weights of IRB banks in 2015Q4, see Finanstilsynet (2016). Risk weights are based on the foundation IRB approach.
3) Risk weights are based on the Basel I framework.
4) Risk weight is calibrated to match a 1% ratio of market risk to total risk-weighted assets in 2015Q4, see Finanstilsynet (2016).
5) Risk weight is calibrated to match a 49% ratio of risk-weighted assets to total assets in 2015Q4.
Sources: Finanstilsynet (Financial Supervisory Authority of Norway), SNL Financial, banking groups' quarterly reports, Statistics Norway and Norges Bank

sudden strain on the position of both enterprises and households. In other times, default shares are linear in the loan rate r_{st} and end of period macro shock z_{t+1}. To quantify the latter relation, we run the following fixed effect regression using data on problem loans:

$$\tilde{P}_{ist} = \tilde{\eta}^s_{0,i} + \tilde{\eta}^s_1 y_{gap,t} + \tilde{\eta}^s_2 \tilde{r}_{ist} + \epsilon_{ist}, \tag{20}$$

where $\tilde{P}_{ist}$ represents bank i's new problem loans in period t to sector s in percent of total lending to the sector. $y_{gap,t}$ represents the output gap for mainland GDP as an indicator for mainland activity.[24] Bank i's annual real lending rate to sector s, $\tilde{r}_{ist}$, is measured in percentage points and based on the reported sector-specific interest rates in ORBOF. $\tilde{\eta}^s_{0,i}$ and $\epsilon^s_{i,t}$ are bank fixed effects and residuals respectively. To account for any seasonal variation, the regression also includes seasonal dummies.

Our empirical measure of the default rates on banks' loans to each sector are based on banks' reported non-performing loans and other loans with a high probability of default, i.e. problem loans. The stock of banks' problem loans is determined by the flow of new problem loans and the flow of problem loans that are either written-off or recovered. Taking the model to the data, the development in the default rates for each sector should reflect the problem loans that lead to loan losses within the period. As an approximation for new defaults, we assume that new problem loans are 30% of the stock of problem loans each quarter. This is in line with the findings of Syversten et al. (2015). They approximate, using data on write-offs and new non-performing loans, the rate of new non-performing loans as a share of the total stock in the period 1996Q1-2015Q2. In this period Norway experienced solid growth and a moderate increase in non-performing loans and credit losses. At crisis impact, the ratio of new non-performing loans is likely to be higher.

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[24]The output gap is calculated as the deviation of the log of real GDP for mainland Norway from a two-sided HP trend using a smoothing parameter of $\lambda = 6400$.

Table 5: Estimation results: New problem loans in percent of lending to the sector

Variable	Corporate	Retail	Customers
$y_{gap,t}$	-0.13***	-0.027***	-0.073***
$r_{i,t}^{L}$	0.07*	0.033**	0.059**
N	364	364	364
Groups	7	7	7

The data covers a panel of the top seven banks over the period 2001Q4-2015Q4. The asterisks denote significance level; * = 10%, ** = 5% and *** = 1%.
Sources: Statistics Norway and Norges Bank

The results for the corporate sector, the retail sector and all customers are reported separately in Table 5. The regression seems to capture the contemporaneous relationship between the level of activity and the level of banks' new problem loans. The effect is stronger for the corporate sector. Banks' lending rates for the respective sectors have a positive and significant effect on new problem loans.

Berge and Boye (2007) find similar effects when looking at driving forces behind developments in the stock of banks' problem loans in Norway. In both the household and enterprise sector, the share of banks' problem loans depends negatively on activity and positively on banks' lending rates. In line with our findings, the effects are much stronger for problem loans to the enterprise sector.

During an average crisis, which lasts about 3 years, we assume that accumulated new problem loans will be about 14% of bank lending. Laeven and Valencia (2012) report the mean peak level of non-performing loans in an international crises database. For 31 OECD countries, reported mean peak level of non-performing loans averages 14% during crisis times in the period 1970-2011. This is close to the 16.4% mean peak of non-performing loans that was observed during the Norwegian banking crisis in the early 1990s, see Laeven and Valencia (2012). To match the ratio of 14%, we assume that new problem loans as a share of total lending rise to 10% at crisis impact ($P_{impact}^{ret} = P_{impact}^{C\&I} = 0.10$). In the remaining years of the crisis, new problem loans to each sector follow the specification given by equation 20.

Regarding loss given default, we assume a common value $\lambda(z_{t+1})$ across sectors. The loss depends partly on the value of banks' collateral and the equity ratios of households and firms. Thus we assume $\lambda(z_{t+1})$ to be state-dependent in the model, see Table 4. For $z_{t+1} \in (z_g, z_b)$ we set $\lambda(z_{t+1})$ to match the long-run average of the ratio of banks' loan losses to new problem loans. In the period 2001Q4-2015Q4, the ratio of banks' loan

losses to new problem loans was about 10%. By determining λ from the data, we also account for the average gain of recovered problem loans and additional realized losses on new problem loans.

For the crisis state, our choice of $\lambda(z_{t+1})$ is in line with established parameters used in Norges Bank's annual stress testing exercise, see Syversten et al. (2015). $\lambda(z_{t+1})$ is set to 30% for both sectors, see Table 4. It follows that at the beginning of the crisis loan losses rise to 3% of total lending.

4.2.2 Banks' capital requirement

In the model, we will focus on the Common Equity Tier 1 (CET1) capital ratio defined as CET1 capital divided by total risk-weighted assets. As a simplification, we use the bank's equity capital as a proxy for the bank's CET1 capital.

Total risk-weighted assets cover banks' credit risk, operational risk and market risk. We note that credit risk is by far the largest component, see Finanstilsynet (2016). In the model, we consider the following simplified implementation of risk-weighted assets:

$$H(L^{ret}, L^{C\&I}, A) = h(L^{ret}, L^{C\&I}) + \omega^A A + \omega(L^{ret} + L^{C\&I} + A) \tag{21}$$

where $h(\cdot)$ corresponds to corporate and retail credit risk and ω^A to market risk. The last term, ω, corresponds to all other risk measures.

With the implementation of the Basel II framework in 2007, banks were allowed to internally calculate risk weights (the IRB approach) for their loan exposures. However, lower limits were set for how much capital could be reduced, see Borchgrevink (2012). The current transitional rule sets a lower limit on the sum of risk-weighted assets applied by IRB banks, which are required to be at least 80% of the risk-weighted assets calculated under the Basel I requirements. Several of the IRB banks are bound by the transitional floor. Therefore, we account for the transitional rule by determining the bank's credit risk on retail and corporate exposures as follows:[25]

$$h(L^{ret}, L^{C\&I}) = \max(\omega^{IRB,ret} L^{ret} + \omega^{IRB,C\&I} L^{C\&I}, 0.80 * (\omega^{B1,ret} L^{ret} + \omega^{B1,C\&I} L^{C\&I})) \tag{22}$$

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[25] As a simplification we assume that all banks fully implement the foundation IRB approach when determining risk weights on loans to the corporate and retail sector. We do not account for risk weights based on the standardized approach or the advanced IRB approach.

where $\omega^{IRB,s}$ is the risk weight on loans to sector s using the IRB approach and $\omega^{B1,s}$ is the risk weight on loans to sector s under Basel I. The risk weights for the IRB approach are based on the reported average risk weights on residential mortgages and corporate loans of Norwegian IRB banks in 2015Q4, see Finanstilsynet (2016) and Table 4. The risk weight on loans to the retail sector under Basel I , denoted by ω_r^{B1}, is set to 50%, reflecting the Basel I risk weight on residential mortgages with a loan-to-value ratio below 80%. ω_c^{B1} is set to 100%, reflecting the Basel I risk weight on corporate loans. In the model, securities are assumed to be safe, but we still add a risk weight noted by ω^A, to capture market risk, which in 2015Q4 amounted to approximately 1% of total risk-weighted assets for IRB banks, see Finanstilsynet (2016).

As a simplification, to account for the components of operational risk and credit risk from exposures other than retail and corporate exposures, we add an additional component to banks' risk-weighted assets as a fixed share of banks' total assets. Given the seven banks' reported mix of assets, the risk weight on banks' total assets, denoted by ω, is set to 7% to match the 49% risk-weighted assets to total assets ratio.[26]

4.2.3 Calibrating banks' loan demand

We parameterize the aggregate loan demand function $L_{st}^A = f_s(r_{st}, z_t)$ as:

$$f_s(r_{st}, z_t) = \exp(\alpha_s + \gamma_s r_{st} + \eta_s z_t) \tag{23}$$

For the aggregate loan demand function, we take the semi-elasticity of demand with respect to the real loan rate from Akram (2014) ($\gamma_{ret} = -3.8$ and $\gamma_{C\&I} = -4.67$) and assume a unit elasticity of demand with respect to the aggregate shock, $\eta_s = 1$. Finally, we normalize the constant term such that when the interest rate equals 3.3% and 3.4%, then loan demand relative to GDP is 3.7 and 2.8 in the household and enterprise sector respectively. These interest rates and ratios corresponds to the sample average over the period 2001Q1 -2015Q4.

For the other credit suppliers response we assume the following functional form:

$$M_s(z_t, L_{st}) = L_{s,*}^o(z_t) - \rho_s(L_{st} - L_{s,*}(z_t)) \tag{24}$$

where $(L_{s,*}^o(z_t), L_{s,*}(z_t))$ are benchmark loan allocations, calibrated such that when the interest rate equals 3.3% and 3.4% in the retail and corporate sector respectively, to-

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[26]According to the banks' annual reports, the ratio of risk-weighted assets to total assets was 49% in 2015Q4.

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tal loan demand in each sector are split between our bank and other credit suppliers according to average market shares over the period 2001Q1-2015Q4. Formally, $L_{st} = L_{s,*}(z_t) \iff L_s^o = L_{s,*}^o(z_t)$ where $L_{ret,*}(z_t) = 0.5 f_{ret}(0.033, z_t)$ and $L_{C\&I,*}(z_t) = 0.4 f_{C\&I}(0.034, z_t)$. The calibration of ρ_s is explained in Section 4.3.

4.2.4 Calibrating loan maturity

In Norway, the average original maturity of mortgages is around 20 years (see Finanstilsynet (2013)). Assuming a uniform distribution of mortgage age structure, the average maturity of mortgages outstanding is 10 years. The ORBOF database provides a time series of the average (across sectors) remaining loan maturity. Assuming a retail loan maturity equal to mortgages (10 years), we can impute the maturity for corporate loans. Given a loan portfolio as in the data, an average of 4 years remaining maturity on corporate loans gives a remaining maturity on the total portfolio as in the data. Hence we set the parameters $m_{ret} = 0.1$ and $m_{C\&I} = 0.25$.

4.2.5 Adjustment cost

The adjustment cost parameter is assumed to be the same across the retail and corporate sector. We set the parameter value such that the magnitude of the adjustment cost relative to average lending in the model is in line with the adjustment cost in De Nicolo et al. (2014). In their dynamic banking model, loan liquidation takes the same functional form as in the present model. However, they apply shorter loan maturity than we do, which all else equal would imply lower loan liquidation costs. Hence we set the parameter to $\psi = 153.8$, which implies that the the adjustment cost associated with reducing loan supply (to both sectors) by 50% from one period to another is the same as in De Nicolo et al. (2014).

4.3 Internal calibration of bank-specific parameters

We determine the remaining parameters $(\rho_{ret}, \rho_{C\&I}, d, \kappa, \beta)$ by matching model simulated moments to corresponding data moments. All data moments are based on the weighted averages of the top seven banks. Specifically, we calibrate the response parameter of other credit suppliers in the retail market (ρ_{ret}) such that we match the interest margin (loan rate net of non-performing loans relative to the deposit rate). For the corporate market we calibrate the response parameter $(\rho_{C\&I})$ such that we match the observed

2015Q4 share of corporate loans to total lending on the banks' balance sheets.[27] The bank's external funding (d) is calibrated to match the observed ratio of securities to total assets[28] in 2015Q4. The fixed cost (κ) is calibrated to match the cost of other net operational costs relative to lending. Other net operational costs include revenue and costs from lease and rental, and equipment expenses. Finally, the bank's discount factor (β) is set to match a nominal return on equity of 12%. This is at the lower end of the reported nominal return on equity of large Norwegian banks in the period 2001-2013, see Aronsen et al. (2014). However, tighter banking regulation and increased equity ratios can lead to reduced return on equity. Aronsen et al. (2014) suggest that it is reasonable to expect that large Norwegian banks have a long-run return on equity of about 12%.

All moments are matched by simulating the model with a fixed capital requirement of 14%. This requirement is somewhat higher than the 12% CET1 capital requirement under Pillar I for systemically important financial institutions in 2015Q4.[29] However, in late 2015, several Norwegian banks continued to build capital to reach announced capital targets in 2016. From 1 July 2016, systemically important banks faced a CET1 capital requirement under Pillar I of 13.5%. In addition, banks had to fulfill individual Pillar II requirements set by the Financial Supervisory Authority of Norway.

We choose to match the observed composition of the top seven banks' balance sheets in 2015Q4. Banks' risk weights and capital requirements have gone through considerable changes in recent years, see discussion in Appendix B. Thus we keep the calibrated model in line with current capital requirements and recent adjustments of the banks' balance sheets as observed in the data, see Appendix C.

Table 6 provides the moments generated by the calibrated model and compares them with the corresponding data moments. We notice that several of the moments are close to their targets.

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[27]Total lending in the data is defined as total lending to customers.

[28]As a simplification, we determine the the top seven banks' share of loans and total securities to total assets by subtracting the amount of short-term lending (cash and claims on other credit institutions) from the banks' assets and short-term borrowing on the liability side.

[29]As the two largest banks in our sample are defined as systemically important, we will also consider the buffer for systemically important banks.

Table 6: The model and the data

Description	Parameters		The data	The model[5)
Share of lending to the corporate sector[1)] (%)	$\rho_{c\&i}$	0.7	32	28
Securities/Total assets[1)] (%)	d	5.64	22	20
Net interest margin, real[1)] (%)	ρ_{ret}	0.95	1.6	1.9
Fixed cost to lending ratio[1)] (%)	κ	0.0112	0.29	0.24
Nominal return on equity[2)] (%)	β	0.955	12	12
Bank risk-weighted assets/total assets[3)]			49	49
Difference in lending rate between sectors[1)]			0.19	1.4
Bank loan losses/gross lending[1)] (%)			0.17	0.19
Std. dev. lending gap/std. dev. output gap[4)]			2.6	2.8
Std. dev. lending gap, retail/std. dev. output gap[4)]			1.5	2.4
Std. dev. lending gap, C&I/std. dev. output gap[4)]			3.7	3.7

Moments below the line correspond to data moments not targeted during the calibration.
1) The sample average is based on the weighted average of the top seven banks. The sample period is 2001Q1-2015Q4. For lending rates and loan losses the sample period is 2001Q4-2015Q4. The bank's balance sheet composition is based on 2015Q4.
2) See Aronsen et al. (2014).
3) Based on the banking groups' quarterly reports. Top seven banks in 2015Q4.
4) Based on all banks and mortgage companies in the period 1992Q1-2015Q4. Gaps are calculated as deviation of the log of variables from a two-sided HP trend with $\lambda = 6400$.
5) The model is simulated over 10 000 periods in the good and bad state.
Sources: Banking groups' quarterly reports, SNL Financials, Statistics Norway and Norges Bank

In the model, the bank faces considerably higher risk weights and loan losses on lending to the corporate sector. Thus, the bank charges a higher loan rate on corporate loans. In line with the data, the model projects a higher optimal lending rate to the corporate sector, see Table 6. However, the interest needed to compensate the bank for lending to the corporate sector is about 1.2 percentage points higher than the observed spread.

The close match of the bank's asset composition in 2015Q4 generates a ratio of total risk-weighted assets close to 49%, see Table 6.

Last, Table 6 shows that the model replicates the more volatile adjustment in bank lending to the corporate sector. Higher volatility of the default share, higher risk weights and shorter maturity on corporate loans contribute to higher volatility of corporate loans in the model.

5 Policy experiments

In this section we perform policy experiments using our calibrated model. We start by considering a model in which the bank faces a zero CET1 capital requirement. Next, we compare the result to our benchmark model specification used in the calibration, in which the CET1 capital requirement is constant at 14%. Our focus is on the bank's ex-ante and ex-post adjustment to crisis shocks. Finally, we run a policy exercise where we allow for a countercyclical capital buffer (CCB). In all policy exercises, the capital requirements are implemented as a hard constraints, implying that violation of the requirement induces liquidation of the bank.

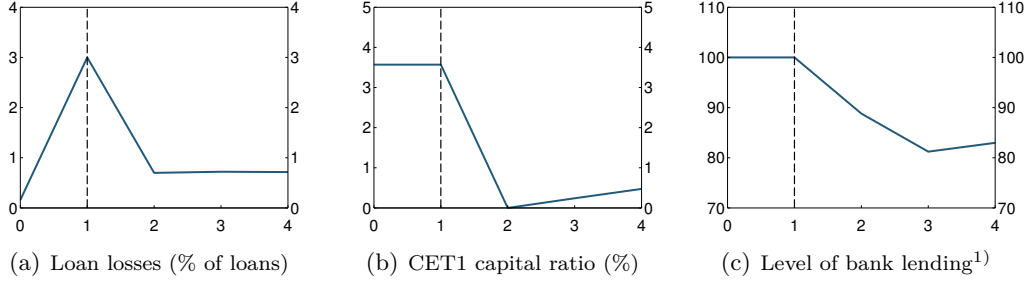## 5.1 The case of a zero capital requirement

First, we explore the bank's behaviour in an economy with a capital requirement of $\phi = 0\%$. The goal is to illustrate bank behaviour in a dynamic framework and the determinants of a voluntary capital buffer. The bank's positive charter value is associated with the fact that it earns positive profits in expectation. In the event of negative equity, the bank is forced to exit and the exit is permanent. Hence, failure implies permanent loss of all future expected dividends. The bank thus has an incentive to accumulate a voluntary capital buffer to protect its charter value.

Figure 3 summarizes the bank's allocation in the good state and the response to a crisis. This is a conditional simulation, in which we have restricted the path for z_t to be in the good state for many periods, before a crisis occurs. Upon crisis impact (which happens with a probability of 4%), the bank faces a large drop in equity as the bank must bear a sharp increase in loan losses. We observe that our calibrated bank accumulates just enough capital in the good state such that it can survive one crisis. Immediately after a crisis shock occurs, equity drops to zero. By keeping a voluntary capital buffer, the bank survives the crisis with positive equity and secures future dividends.

We define a bank that cannot survive a crisis as an undercapitalized bank. Note that the pre-crisis behaviour in Figure 3 illustrates the bank's allocations when it has been in the good state for several years. From Figure 3, we can conclude that if the bank is in the good state for a longer period, it will voluntarily accumulate enough capital to avoid being undercapitalized in a future crisis and thus secure future dividends.

However, in an unconditional simulation (i.e. no restrictions on the z_t path) the bank experiences crisis shocks while being undercapitalized. We observe that the bank does not find it optimal to hold enough capital to cover more severe crises, i.e. a new crisis

Figure 3: The bank's response to a crisis with a zero CET1 capital requirment

(a) Loan losses (% of loans)   (b) CET1 capital ratio (%)   (c) Level of bank lending[1]

1) We normalize the level of bank lending such that lending in the good state with a zero CET1 capital requirement = 100.

following soon after the first crisis episode. By simulating the model over many periods[30] we find that in close to 4% of the crises the bank is forced to exit the market. In these crises, the bank experiences a sharp increase in loan losses while being undercapitalized. This result follows from the two key frictions, a high discount factor and slow moving equity (see Section 3), both of which are necessary. (*i*) Since accumulating capital is costly, the bank does not find it optimal to accumulate enough capital to completely avoid exit. (*ii*) Since new equity issuance is prohibitively expensive, the bank cannot recapitalize once equity turns negative. In all exit events, the bank exits under limited liability. Although not explicitly modelled, exit under limited liability will ultimately impose an implicit cost on taxpayers, who have to cover bank liabilities.

Interestingly, Figure 3 shows that in the aftermath of a crisis impact, loan supply first drops sharply, then gradually increases in line with the bank's equity capital. This is due to the fact that the bank acts in a precautionary manner. The risk of a new crisis in the immediate future leads the bank to hold back on lending while it rebuilds capital. The bank temporarily self-insures by switching from risky loans to safe securities.

To summarize, in the absence of a regulatory capital requirement, the bank finds it optimal to keep a voluntary buffer. This buffer is clearly affected by the probability and the consequence of a crisis. In our model, a severe crisis can be defined as a double-dip in which the economy returns to the crisis state soon after recovery. A severe crisis is enough to force the bank to exit the market. However, as these events are rare, the bank does not find it optimal to insure against all potential future exits by further limiting dividends today.

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[30]We generate 10 000 repetitions of the length T, where $T = \max\{exitperiod, 1000\}$.

5.2 Introducing a positive capital requirement

Next, we introduce a positive capital requirement of $\phi = 14\%$. We note that this capital requirement is considerably higher than the bank's voluntary capital buffer in the previous exercise.

Figure 4: The bank's response to a crisis with a 14% CET1 capital requirement
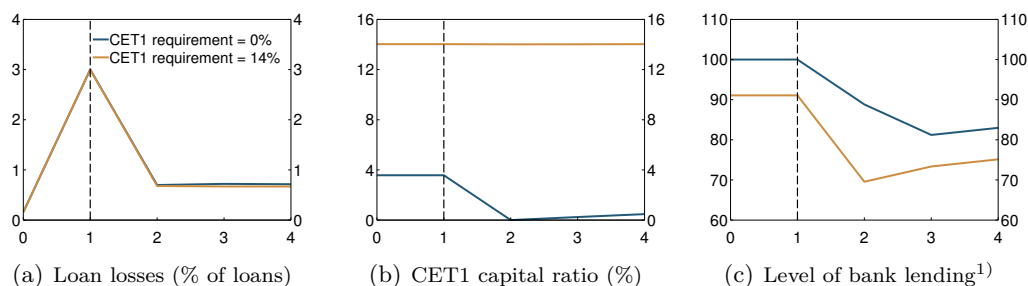
(a) Loan losses (% of loans)   (b) CET1 capital ratio (%)   (c) Level of bank lending[1]

1) We normalize the level of bank lending such that lending in the good state with a zero CET1 capital requirement = 100.

Figure 4 illustrates the bank's adjustment to a crisis with a zero and a 14% CET1 capital requirement. The introduction of a regulatory capital requirement changes the bank's optimal adjustment in several ways, see Figure 4. First, the bank's CET1 capital ratio is close to the capital requirement in all states. Second, in the good state, the bank finds it optimal to adjust to the capital requirement by accumulating more equity capital and holding a smaller volume of loans.[31] Consequently, since accumulating capital is costly, the bank does not find it optimal to go all the way to the equity level that is required to maintain the same loan supply as in the case with a zero capital requirement. Third, the crisis leads to a sharp contraction in the bank's lending. At crisis impact, the bank experiences a sharp increase in loan losses, which erodes the bank's equity by about 23%. This is considerably smaller than with a zero capital requirement, in which case the crisis shock leads to a 100% depletion of equity capital. To keep satisfying the CET1 capital requirement in the crisis when $\phi = 14\%$, the bank tightens lending more than when $\phi = 0\%$. The reason the bank no longer holds a voluntary buffer above the requirement when $\phi = 14\%$ is that the failure risk is essentially zero. Note however, that as bank profits are concave in lending (due to market power and adjustment cost in

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[31]In comparison with international evidence of a 1 percentage point increase in the capital requirement reported in Basel Committee on Banking Supervision (2010c), an increase in the capital requirement of from 14% to 15% reduces our bank's loan supply by 2.1%. This is within the range of estimates reported in Basel Committee on Banking Supervision (2010c).

lending), the need to quickly tighten lending in a crisis entails a cost to the bank. The tightening could have been avoided by accumulating a voluntary capital buffer above the CET1 capital requirement in the good state. However, given the calibrated likelihood of a crisis and the cost of a large lending contraction in a crisis, the expected cost of a large lending contraction does not outweigh the cost of holding a voluntary buffer in the good state.

Compared to bank behaviour with a zero capital requirement, we observe that a 14% capital requirement induces both lower lending in normal times and a sharper contraction upon crisis impact. However, the bank is more resilient when the capital requirement is 14% and the exit probability conditional on a crisis is essentially zero, compared to 4% with a zero capital requirement.[32]

5.3 Introducing a dynamic capital requirement

The previous sections illustrate that introducing a positive capital requirement makes the bank more resilient to exit. However, since the bank does not accumulate a voluntary buffer above the capital requirement, lending contracts more at crisis impact. This could potentially be mitigated by introducing a time-varying capital requirement. In this section we thus explore bank behaviour when facing a countercyclical capital buffer (CCB) and compare it to the bank's behaviour with a fixed capital requirement (noCCB).

In line with current regulation, the countercyclical capital buffer can normally vary between 0% and 2.5%. From 30 June 2016, other CET1 capital requirements for systemically important financial institutions under Pillar I totalled 12%, hence we assume that the CET1 capital requirement with the CCB will vary between 12% and 14.5%.[33] In the model, financial vulnerabilities are associated with the exogenous Markov process z_t. Thus, when implementing the CCB we assume a buffer requirement of 2.5% in normal times, hence $\phi^{CCB}(z_t) = 14.5\%$ when $z_t \in (z_g, z_b)$, and a full decrease in the buffer requirement to 0% during crisis, $\phi^{CCB}(z_t) = 12.0\%$ when $z_t \in (z_c)$. In addition,

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[32]In a comparison between a zero and a 7% capital requirement, we find that the bank adjusts by increasing capital and holding a smaller volume of loans. However, the bank does not adjust the balance sheet to the same extent as with a 14% capital requirement. Moreover, the bank finds it optimal to hold a voluntary buffer of 1% above the capital requirement, which is lower than with $\phi = 0\%$ but higher than with $\phi = 14\%$. In addition, a 7% capital requirement is not sufficiently high to completely avoid exit as there is still a positive exit probability conditional on crisis of 0.15%.

[33]From 30 June 2016, the Common Equity Tier 1 (CET1) capital requirement for Norwegian systemically important financial institutions under Pillar 1 was 13.5%, consisting of a CCB of 1.5%, a buffer for systemically important banks of 2%, a systemic risk buffer of 3%, a conservation buffer of 2.5% and a minimum requirement of 4.5%.

we assume that the buffer requirement remains off after recovery from a crisis until the economy reaches the good state. This will leave the bank at least one year to prepare for the higher capital requirement. Remember that after recovery from a crisis, the economy first enters the bad state, see Section 4. Formally, we define this state as z_b^p, which denotes bad states that follow immediately after crisis states and last until z_t, goes back to either z_g or z_c. It follows that the CCB capital requirement in state z_t follows the specification:

$$\phi_t^{CCB} \quad = \quad \begin{cases} 14.5\% & if \quad z_t \in z_g, z_b \\ 12.0\% & if \quad z_t \in z_c, z_b^p \end{cases} \tag{25}$$

In the noCCB regime, the constant capital buffer is set such that the capital requirement corresponds to the long-term capital requirement in the CCB regime. The goal is to illustrate the potential gain and costs of having a time-varying buffer and not a long-term higher or lower capital requirement. Based on the transition probability matrix in equation (18) in Section 4, the long-term capital buffer in the CCB regime is about 1.8%. Hence, we set $\phi^{noCCB}(z_t) = 13.8\%$ in the noCCB regime.
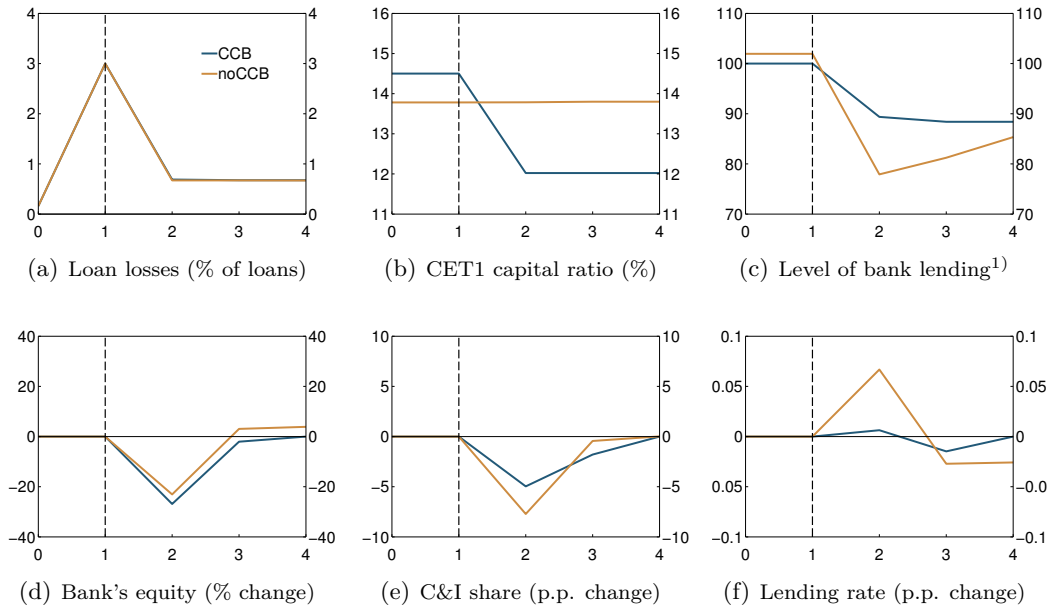
Figure 5 summarizes the bank's adjustment to a crisis with a countercyclical and a constant capital requirement. At crisis impact, the bank experiences a sharp increase in loan losses, which erodes the bank's equity through negative profits by about 22% in the CCB regime and 23% in the noCCB regime.[34] To satisfy the CET1 capital requirement, the bank tightens lending. In the case with a fixed capital requirement, the bank delevers by a sharp contraction in lending. With the CCB, the bank receives a 2.5 percentage point easing in the capital requirement when the crisis occurs. The decreased requirement reduces the need to tighten lending, see Figure 5. Moreover, higher loan losses and risk weights on loans to the corporate sector induce a sharper contraction in lending to the corporate market under both policy regimes, see Figure 5.

To evaluate the effects of the CCB more generally we also compute unconditional moments, letting the $z-$shock fluctuate according to the transition matrix in equation 18, see Section 4. Table 7 shows average lending (in crisis and normal times), the CET1 capital ratio, volatility of lending relative to the volatility of GDP, and the fall in bank lending at crisis impact across the two regulatory regimes.

Overall we see that the CCB regime generates less contraction in lending in a crisis

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[34]In Figure 5d with the CCB, the bank's equity falls 22% due to negative profits and by an additional 5 percentage points due to the lower CET1 requirement and positive dividend paid out by the bank.

Figure 5: The bank's response to a crisis with a countercyclical capital requirement (CCB) and a fixed capital requirement (noCCB)

(a) Loan losses (% of loans) (b) CET1 capital ratio (%) (c) Level of bank lending[1]

(d) Bank's equity (% change) (e) C&I share (p.p. change) (f) Lending rate (p.p. change)

1) We normalize the level of bank lending such that lending in the good state with the CCB = 100.

and substantially lower volatility. The reduced volatility in bank lending is mainly due to higher crisis level lending under the CCB regime. In addition, the CCB regime stimulates lending upon recovery from a crisis, when the bank's capital level is still relatively low and return on lending has returned to the normal times level.

However, by removing the buffer, the CCB regime is more vulnerable to a severe crisis. Figure 6 illustrates the bank's adjustment if the CET1 requirement is at 12% when the crisis hits. In this case, the bank will not receive a further relaxation of the capital requirement and will be forced to tighten lending to roughly the same level as in the noCCB regime. As loans adjust from an initially higher level in the CCB regime, the contraction in lending is larger than with the fixed capital requirement. Given the transition probability matrix, about 14% of the crises will have a sharp contraction in lending due to a double dip, see Table 7.

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Table 7: Comparing the effects of a countercyclical capital requirement (CCB) and a
fixed capital requirement (noCCB)

	CCB	noCCB
CET1 capital ratio (%), crisis states	12	13.8
CET1 capital ratio (%), good and bad states[2]	14.5	13.8
Level of bank lending[1], crisis states	91	84
Level of bank lending[1], good and bad states[2]	101	103
Standard deviation[3]	3.7	5.5
Fall in bank lending, crisis impact (%)	-10	-24
Severe contraction in bank lending[4] (% of crises)	14	100

Based on the bank's adjustment in the good, bad and crisis state. The model is simulated over 10 000 periods.
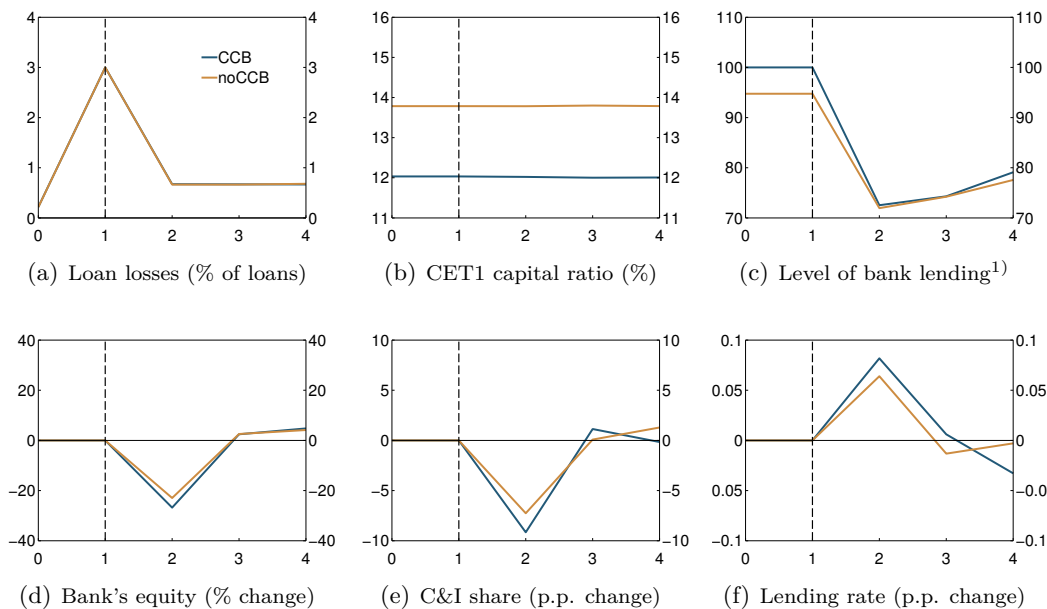1) We normalize the level of bank lending such that the average loan level across all three states with the CCB = 100.
2) Excluding bad states that follows after a crisis ($z_b \neq z_b^p$).
3) Standard deviation of the lending gap/standard deviation of the output gap. The lending gap is the percentage deviation of lending from the mean. The output gap is the percentage deviation from trend.
4) Severe contraction is here defined as a 15% fall in bank lending at crisis impact.

Figure 6: The bank's response to a crisis with a zero countercyclical capital buffer
(CCB) and a fixed capital requirement (noCCB)

(a) Loan losses (% of loans)   (b) CET1 capital ratio (%)   (c) Level of bank lending[1]

(d) Bank's equity (% change)   (e) C&I share (p.p. change)   (f) Lending rate (p.p. change)

1) We normalize the level of bank lending such that lending in the bad state (z_b^p) with CCB = 100.

5.3.1 The sensitivity of the baseline assumptions

The previous sections illustrated the benefits and costs associated with a positive capital requirement and the potential gain if this requirement varies over the cycle. However, the effect of the countercyclical buffer depends on several assumptions in the model. In this section we explore the effect of (i) a sharper contraction in credit demand during a crisis and (ii) allowing the bank to issue new equity by relaxing the non-negativity constraint on dividends and (iii) the role of bank rationality. Table 8 summarizes the effect of the CCB if we change the baseline assumptions. We evaluate the volatility of lending relative to the volatility of GDP and the fall in bank lending at crisis impact.

In alternative scenario (i) it is assumed that the fall in loan demand is so severe that it will dampen the effect of the CCB. Lower loan demand will contribute to a sharp decline in bank lending, with or without the countercyclical capital buffer. However, the volatility in lending in the CCB regime is somewhat lower, due to the fact that the bank can reduce lending more gradually, and thus reduce adjustment costs. In addition the buffer is set to zero during the recovery phase, which boosts lending compared to the noCCB regime.

The effect of the CCB is also influenced by the bank's ability to raise new equity. In alternative scenario (ii), we remove the non-negativity constraint on dividends, allowing the bank to raise capital beyond retained earnings. Implicitly, we assume that issuing new equity by paying negative dividends is as costly as raising capital by retaining earnings. This is an extreme assumption, in particular in a crisis. In the periods when capital is raised, the bank will suffer a negative dividend stream. Table 8 shows that the bank will choose to raise new equity at crisis impact if the capital requirement is constant. In addition, the bank facing a countercyclical capital requirement will raise new equity in the case of a severe crisis. By avoiding a sharp contraction in lending, the bank can reap a higher dividend stream in the succeeding years and reduce potential adjustment costs.

Finally, behaviour is also affected by the bank's perception of the probability, the consequence and the duration of a crisis. To illustrate the effects of the bank's expectations we distinguish between two types of banks: A myopic bank and an optimistic bank. We assume that the myopic bank underestimates the probability of going from normal times to a crisis, but understands the true probability of staying in the crisis when it occurs. Similarly, the optimistic bank underestimates the probability of crisis, but once in a crisis, it expects the crisis to be short-lived.

Table 8: Changing baseline assumptions: The effect of the cyclical capital requirement

			Standard deviation[1]	Fall in bank lending, crisis impact (%)
	Baseline	CCB	3.7	-10
		noCCB	5.5	-24
(i)	Severe fall in credit demand	CCB	6.8	-18
	and higher NPLs	noCCB	7.3	-24
(ii)	The bank can raise equity through	CCB	3.2	-9
	negative dividend	noCCB	3.7	-11
(iii)	Myopic expectations	CCB	5.2	-17
		noCCB	6.4	-25
(iii)	Optimistic expectations	CCB	3.8	-12
		noCCB	6.3	-25

Based on the bank's adjustment in the good, bad and crisis state. The model is simulated over 10 000 periods.
1) Standard deviation of the lending gap/standard deviation of the output gap. The lending gap is the percentage deviation of lending from the mean. The output gap is the percentage deviation from trend.

Figure 7: Changing expectations: The bank's response to a crisis with a cyclical capital requirement (CCB) and a fixed capital requirement (noCCB)

(a) Loan losses (% of loans)   (b) CET1 capital ratio (%)   (c) Level of bank lending[1]
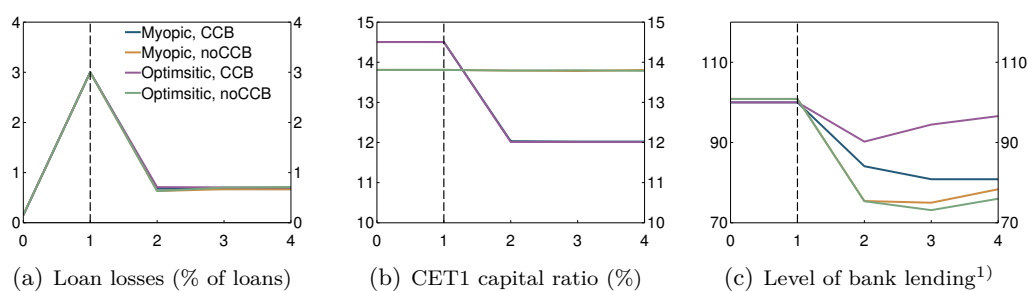
1) We normalize the level of bank lending such that lending in the good state with the CCB = 100.

In the good state, both types of bank underestimate the probability of crisis and take on higher credit risk by expanding lending. At crisis impact the bank's equity erodes by about 2 percentage points more than in the baseline model. The bank with a fixed capital requirement, regardless of expectations, reduces lending sharply. However, once in a crisis, the bank's optimal level of lending is crucially determined by expectations. The optimistic bank expects less credit risk and would like to maintain a high share of loans on the balance sheet. In contrast, the myopic bank expects higher credit risk and would like to switch from risky loans to safe securities. Consequently, since capital levels for both types of banks are equally depressed after crisis impact, the optimistic bank's loan supply responds more to the reduction in capital requirement imposed by the CCB regime, as shown in Figure 7. It follows that the effect of the CCB is considerably larger in the case of the optimistic bank, see Table 8. As the myopic bank wants to tighten lending during the crisis, the only benefit of the CCB is reduced adjustment costs. In the case of the optimistic bank, reducing the CCB avoids a sharp contraction in lending. However, the fact that the optimistic bank systematically underestimates the severity of a crisis will inflict higher loan losses in all crisis periods.

6   Summary

In this paper we have presented a dynamic model of bank behaviour over the business cycle and investigated the effects of a countercyclical capital requirement.

We show that in a model with a zero CET1 capital requirement, the bank optimally holds a voluntary countercyclical buffer to self-insure against negative shocks. However, the bank is still subject to failure risk, in the event of severe crises. In contrast, fixing the capital requirement at a high level removes failure risk but induces higher volatility in lending since the bank does not accumulate a voluntary buffer above the requirement. Hence a regime with a time-varying capital buffer imposed on a sufficiently high capital requirement level dampens the regulatory-induced fluctuations in lending. However, decreasing the buffer in a crisis entails a cost as the bank becomes more vulnerable to new negative shocks.

Furthermore, we show that the effect of the countercyclical capital buffer depends on the assumptions in the model. Lower credit demand will contribute to a sharp decline in the bank's lending, with or without the countercyclical capital buffer. The effect of the countercyclical buffer will also be weaker if the bank opts to improve capital ratios in ways other than by restricting lending. Finally, we find that the CCB will lead to

smaller fluctuations in lending if the bank believes that crises are short-lived. In the case of a myopic bank, a crisis will lead to a negative shift in expected returns and the bank will tighten lending even if the capital requirement is reduced.

The bank's adjustment under the two policy scenarios illustrates the effects of a time-varying capital requirement, but the analysis does not indicate an appropriate level for the capital requirements.

A   Appendix: Banking data

Banking data at the micro level provides valuable information on how banks adjust to economic developments. In Norway, the main source of micro data on banks' balance sheets is banks' financial statements. Using financial statements to analyze banks' behaviour creates considerable challenges. There have been several structural and regulatory changes in the Norwegian banking sector. These changes affect both the behaviour of banks and the reported measures of banks' balance sheets and income statements. A central challenge is to separate and identify these effects. The increased complexity of the banking sector and the lack of historically consolidated data have made it necessary to collect data from several sources.

The data has been collected from three main sources: Banks and financial undertakings' financial reporting to Norwegian authorities ("Offentlig regnskapsrapportering for banker og finansieringsforetak (ORBOF)"), SNL Financial and OECD banking statistics.

All reports on banks' balance sheets to ORBOF are reported at the parent bank level and cover the period 1987Q1-2015Q4.[35] The data covers all Norwegian banks and mortgage companies. The ORBOF data provides a consistent description of each bank's balance sheet components over the sample period. However, volumes are effected by the increase of cross-exposures and transfers within each banking group. Specifically, the introduction of Norwegian covered bonds[36] in June 2007 resulted in a gradual decrease in lending from parent banks' balance sheets and an equivalent increase in lending from banks' fully or jointly owned mortgage companies, see Bakke et al. (2010) and Figure 8. When analyzing Norwegian banks' behaviour, it is necessary to account for the adjustment in all loans, including those that are transferred to mortgage companies.

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[35]Quarterly data on banks' non-performing loans and other loans with a high probability of default covers the period 1992Q1-2015Q4 and quarterly data on banks' interest rates covers the period 2001Q4-2015Q4.

[36]Norwegian covered bonds are debt instruments issued by covered bond mortgage companies and secured on residential or commercial mortgages. The mortgage companies are owned by banks.

Figure 8: Lending from Norwegian banks and mortgage companies to customers.
Lending in billions NOK. 1987Q1-2015Q4
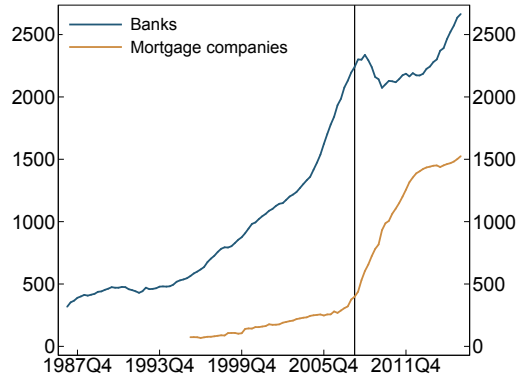
The data from SNL Financial covers a shorter time period 2008Q1-2015Q4 and is reported at banking group level. The banking group data includes fully owned mortgage companies. Ideally, we would use the SNL banking group data for the entire period of interest for all Norwegian banks. However, the SNL banking group data is limited both with respect to the sample, the number of Norwegian banks covered and the granularity of the data. Thus, we combine the consistent history of the ORBOF data with the group level data from SNL Financial. The panel dataset is constructed as follows:

1. Available SNL financial data at banking group level is applied in the period 2008Q1-2015Q4.

2. We take advantage of the fact that the volume of transferred loans is limited in 2008 and append the main balance sheet components using the ORBOF data in the period 1987Q1-2007Q4, see Figure 8.

3. From the ORBOF database, we include information on banks' non-performing loans and other loans with a high probability of default, lending rates and lending by sector, such as lending to the retail and corporate sector.

4. For banks that are not included in the SNL Financial data, we apply the ORBOF data on banks' balance sheets. The balance sheets of fully owned mortgage companies that issue covered bonds are aggregated with the parent bank's balance sheet. Some mortgage companies are owned jointly by several banks. We take advantage

of data on the balance sheet of the two largest jointly owned mortgage companies that issue covered bonds.[37] The balance sheet items of the jointly owned mortgage companies are aggregated with the parent banks' balance sheet according to each bank's transferred loans to covered bond mortgage companies as reported by ORBOF.[38] Finally, we try to limit the cross-exposures within a banking group when aggregating the balance sheet across a banking unit and a fully or jointly owned covered bond mortgage company.[39]

Even though the constructed dataset has several improved features compared with the raw ORBOF dataset, there are still several weaknesses that are not accounted for by this procedure. First, the information on the cross-exposures between parent bank and fully or jointly owned mortgage companies is clearly limited. Several internal cross-exposures are still present when we aggregate balance sheets based on the ORBOF data. Second, several of the smaller jointly owned covered bond mortgage companies are not included. This can lead to breaks in the time series of balance sheet components for some banks. Last, the SNL Financial data includes the banking groups' foreign branches and subsidiaries abroad, which are not included in the ORBOF data. This creates a systematic deviation when comparing the SNL Financial and ORBOF data. When comparing banks' lending to customers, the ORBOF data is used as the only source of information. This is the case when determining the banks' size and analyzing banks' non-performing loans and other loans with a high probability of default.

Finally, when focusing on aggregate developments in the banking sector over time, we take advantage of longer time series as reported in the OECD's banking statistics. The aggregated balance sheet components are appended with the aggregated OECD data for the period 1980-1986. The annual OECD data is converted to quarterly by linear interpolation.

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[37]These covered bond mortgage companies are SpareBank 1 Boligkreditt AS and Eika BoligKreditt AS.

[38]The same procedure is applied to banks that are covered by the SNL financial and transfer loans to jointly owned covered bond mortgage company.

[39]If the parents banks' covered bond is issued by a company within the banking group or an attached company, the covered bond is eliminated on the respective asset and liability side.

B Appendix: Banks' equity ratio over the financial cycle

In Section 2 we showed that Norwegian banks appear to look though the business cycle when adjusting their equity ratio. Here we focus on the medium-term properties of banks' balance sheets and document how the banks' adjust their equity ratio with the booms and busts in credit and with the implementation of the Basel capital frameworks in Norway.[40]

In addition to adjusting over the business cycle, banks may also respond to the longer-term outlook of the economy as it takes time to adjust some balance sheet positions. If a boom or bust is assumed to be short-lived, banks may "look through" these periods. Borio et al. (2001) suggest that in some business cycle booms financial market participants underestimate risk, which leads to excessive credit growth. These credit-intensive booms can be more damaging as they often end with financial distress and severe contractions in credit, see Jordà et al. (2013) and Schularick and Taylor (2012).

We apply the HP filter to separate the time series into a cyclical and a trend component. For the financial cycle (lasting 10-20 years), we follow the suggestion of the Basel Committee on Banking Supervision (2010a) and choose a λ equal to 400 000. As an indicator of the booms and busts in credit, we use the percentage point deviation of total credit-to-GDP from trend (the credit-to-GDP gap). Total credit is the sum of domestic credit to households and total credit to non-financial enterprises for mainland Norway.[41]

The data indicates that banks' equity ratio is countercyclical with respect to the credit-to-GDP gap, see Figure 9a. In the sample period, the cyclical component of banks' equity ratio decreases as credit booms. The equity ratio increases again as the credit-to-GDP gap begins to decline. Shin and Shin (2011) suggest the risk management policies of financial intermediaries as a possible explanation of the countercyclical equity ratio. If perceived risk is low in expansions and high in contractions, and banks aim to keep sufficient capital to meets their overall value at risk, it follows that the equity ratio is countercyclical. Borio et al. (2001) argues that difficulties of measuring the build-up of risk during credit booms, as market participants extrapolate current market conditions into the future, leads to financial institutions holding relatively low capital. In combination with inflated collateral values and artificially low lending spreads, these

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[40]Several studies emphasize the importance of considering the medium term when characterizing the cyclical pattern of financial variables, see Drehmann et al. (2012) and Aikman et al. (2015).

[41]Total credit to non-financial enterprises comprises domestic credit non-financial enterprises and foreign debt for mainland Norway. Total credit covers both loans and debt securities.

Figure 9: The medium-term cyclical[1] component of banks' equity ratio[2]
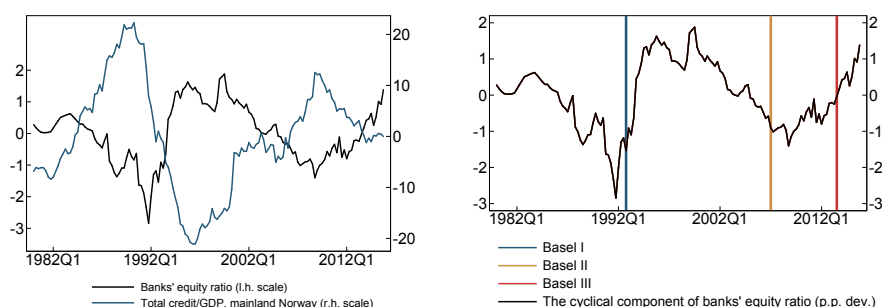
(a) Banks' equity ratio and the credit-to-GDP gap

(b) Banks' equity ratio and implementation of the Basel capital frameworks

1) Percentage point deviation from estimated trend. The trend is estimated using a two-sided HP filter with lambda=400 000.
2) Excluding foreign branches.
Sources: OECD, SNL Financial, Statistics Norway and Norges Bank

financial developments may play a major role in the extended booms and busts of credit.

We also recognize that capital regulation can be an important factor in how banks adjust their equity ratio. Figure 9b shows the implementation of the Basel capital frameworks in Norway.[42] Basel I was enforced for banks and mortgage companies in Norway by the end of 1992, see Haare et al. (2015). All banks and mortgage companies had to fulfill a minimum requirement of regulatory capital equal to 8 % of risk-weighted assets.[43] Figure 9b shows that banks did on average increase their equity ratio in the early 1990s. In 2007, the Basel II capital framework was introduced and led to considerable changes in the risk weights on banks' assets, see Andersen (2013) and Haare et al. (2015). Banks could now choose between standardized risk weights and risk weights calculated using the Internal Ratings-Based (IRB) approach. For IRB banks, risk weights generally dropped for both mortgages and corporate loans.[44] The transition from Basel I to Basel II was accompanied by a fall in the medium-term cyclical component of banks' equity ratio, see Figure 9b. In 2013, the recommendations in Basel III were implemented in Norway, see Norges Bank (2013) and Basel Committee on Banking Supervision (2010b). In recent years, the phasing in of the capital and buffer requirements of the EU capital

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[42]These international regulatory frameworks for banks are recommendations of the Basel Committee on Banking Supervision.

[43]The requirement was not necessarily a tightening for the individual bank due to the new measure of banks' risk-weighted assets, see Haare et al. (2015).

[44]For the standardized approach, Basel II led to a reduction in risk weights on residential mortgages to 35% on highly secured loans.

framework (CRR/CRD IV) has been accompanied by an increase in banks' equity ratio, see Figure 9b and Winje and Turtveit (2014).

# C Appendix: Banks' balance sheet composition

Here we document the composition of Norwegian banks' balance sheets. We illustrate the variation in balance sheet ratios across banks in the period 1987Q1-2015Q4. We compare the variation across all Norwegian banks and the seven largest banks (by to total loan volume to the Norwegian corporate and retail sector) in Norway. We exploit both the constructed dataset described in Appendix A and the raw ORBOF database. For measures such as banks' equity ratio and wholesale funding ratio we exclude foreign branches.

The heterogeneity across banks is illustrated by sorting all observations of banks' key balance sheet ratios from the highest to the lowest. We plot the developments in the median, the 70% and the 90% of observations that are closest to the median, see Figure 10. For the largest banks in the Norwegian market for loans, we use the weighted mean of the top seven banks. We use the real time structure of banking institutions. Thus, the top seven banks only correspond to the calibration's targeted top seven banks in recent years in Figure 10a and 10b, see discussion in Section 4. Figure 10c and 10d include foreign branches.

Our rich data set indicates several sources of heterogeneity in the banking sector, see Figure 10. First, the seven largest banks have on average a lower equity ratio, lend more to the corporate market and have a larger share of wholesale funding than the majority of smaller banks.

Second, we notice that the variation in banks' mix of loans has gradually decreased in the sample period and the data indicates a gradual shift in banks' relative exposure towards the retail sector.

Figure 10: Norwegian banks' balance sheet composition. 1987Q1 - 2015Q4

(a) Equity ratio[1] (%)

(b) Wholesale funding ratio[1] (%)

(c) Loans to the retail sector[2] (%)

(d) Loans to the corporate sector[2] (%)
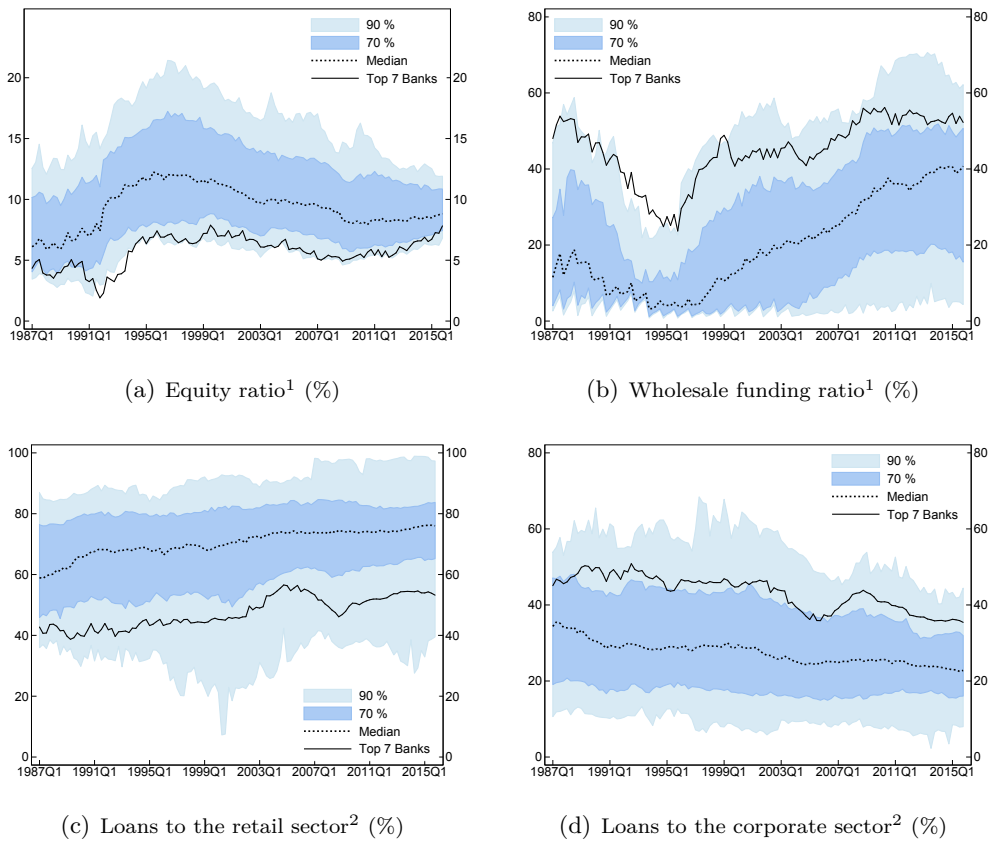
1) Measured in percent of total assets. Excluding foreign branches.
2) Measured in percent of total lending to customers.
Sources: SNL Financial, Statistics Norway and Norges Bank

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