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Countercyclical Capital Buffer Proposal: an Analysis for Norway*

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Abstract

This paper evaluates the ability of some macro variables, namely GDP growth, credit growth, credit to GDP ratio and property prices in guiding the accumulation of a capital buffer above the minimum during the credit expansion episode in Norway. We use two performance benchmarks. First, we evaluate their performance based on their skill in signalling a financial crisis. Second, we compare their performance on the basis of their correlation with a measure of the banking system's vulnerability. The main conclusion we derive from the analysis is that the credit to GDP ratio has the best performance. Moreover, data limitations seriously affect the usefulness of the Norwegian residential property price as banking crisis indicator.

1 Introduction

The current financial crisis revives the debate on the necessity of mitigating procyclicality of the financial system. The Basel Committee states in the December 2009 Consultative Document "*Strengthening the resilience of the banking sector*" that measures to address procyclicality should achieve four key objectives:

- dampen any excess cyclicality of the minimum capital requirement

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- promote more forward looking provisions
- conserve capital to build buffers at individual banks and the banking sector that can be used in distress
- achieve the broader macroprudential goal of protecting the banking sector from periods of excess credit growth

A proposal on countercyclical capital buffer is designed with the aim to address the fourth objective. One of main issues involved in the design process is the choice of conditioning variables that can guide the buildup of the buffer during the periods of credit expansions. In this paper, we will assess the ability of some macrovariables, namely GDP growth, credit growth, credit to GDP ratio and property prices in reflecting the risk build up inside the banking system in Norway. We use two performance benchmarks. First, we evaluate their performance based on their skill in signaling a financial crisis. Second, we compare their performance on the basis of their correlation with a measure of the banking system's vulnerability. The main conclusion we derive from the analysis is that the credit to GDP ratio has the best performance. Moreover, data limitations seriously affect the usefulness of the Norwegian residential property price as a banking crisis indicator.

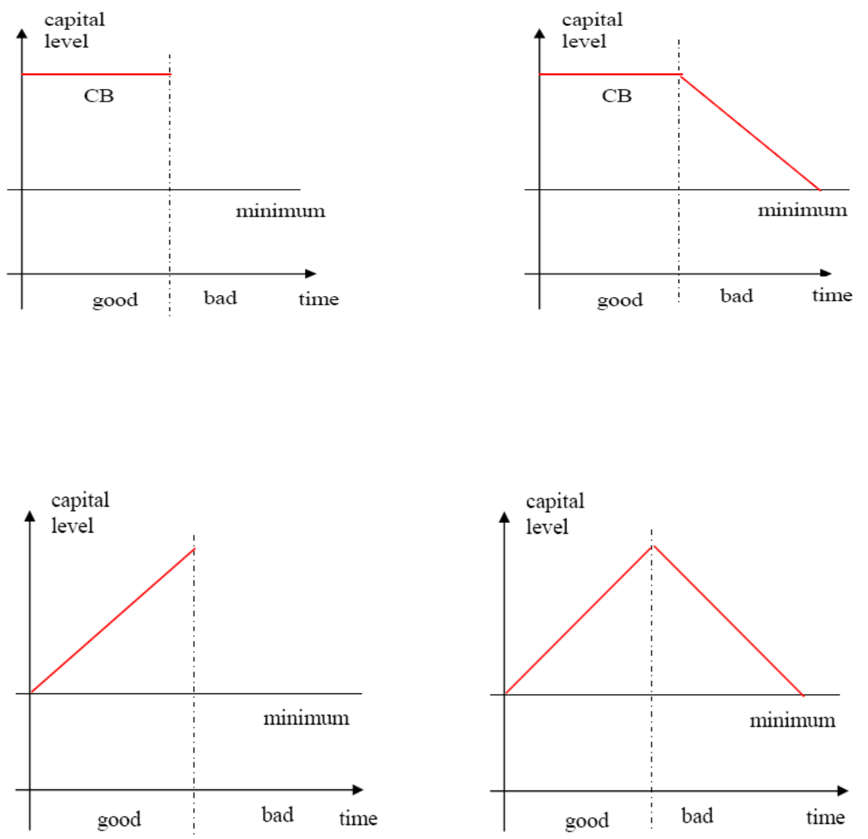
The paper is organized as follows. In the next section, we briefly present the main components of the countercyclical capital buffer proposal and the issues involved in the design process. Then, we describe in the section 3 the data we use for our analysis. Section 4 compares the performance of different conditioning variables by using the signals approach. In the section 5, we provide another performance assessment based on the bank risk index. Finally, section 6 concludes.

2 Countercyclical Capital Buffer: an Overview

The countercyclical capital buffer scheme involves a mechanism to build up, in the banking system during strong economic conditions, a capital buffer which is allowed to be run down when generalised adverse conditions materialise. This capital buffer constitutes a *free* capital base that is available to absorb losses in a stressful environment without causing a credit contraction.

The countercyclical capital buffer constitutes one of macroprudential tools proposed by BCBS to address the procyclicality of the financial system. Its primary aim, as stated in the BIS consultative paper, is to use a buffer of capital to protect the banking sector from periods of excessive aggregate credit growth which have often been associated with the buildup of system-wide risk. It is expected to help ensure that the banking sector in aggregate has the capital on hand to maintain the flow of credit in the economy without its solvency being questioned, when the broader financial system experiences stress after a period of excess credit growth.

Different schemes can be considered. One extreme form would be to set a fixed buffer above the minimum during good times and require no buffer during bad times. Alternatively, we could require an increasing buffer in good times by relating it to some conditioning variables and then let the buffer decrease gradually in bad times. In fact, four combinations are possible as shown in the following figures:



To make a countercyclical capital buffer scheme operational, a number of terms must be determined. First, we have to define some indicators which can signal the transition from good to bad times (transition variables). Second, we need to choose variables that can effectively act as guides for the speed of the accumulation and release of the buffer (conditioning variables). Finally, a benchmark minimum capital requirement should be defined.

A natural candidate for the third step is the Basel III minimum. In the BIS consultative paper (July 2010), the countercyclical capital buffer proposal is presented as an extension of the capital conservation buffer which is established above the regulatory minimum Tier 1 so that capital distribution constraints will be imposed on the bank when capital levels fall within this range.

The transition variables and conditioning variables can be the same or different variables. Given that the countercyclical capital buffer serves to reduce the risk of the supply of credit being constrained, intuitively, the release of this buffer should be allowed once the banking system as a whole records high losses. Principle 4 of the current BIS proposal states that promptly releasing the buffer can be done by timing and pacing the release of the buffer with the publication of banking system financial results so that the buffer is reduced in tandem with the banking sector's use of capital to absorb losses or its need to absorb an increase in risk weighted assets. Note that the use of banks' losses to trigger the release may have positive incentive effects in correcting the banks' incentive for delaying the report of losses. However, gross losses are not a good indicator to signal the size of capital buffer accumulated in good time. Indeed, the capital buffer above the minimum serves as insurance against the future loss associated with the risk built up in a boom period. Hence, the accumulation of the buffer should be guided by some variables that can reflect imbalances inherent with the economic development. In this sense, gross losses measured as actual losses recorded in the banking system are not the right candidate because of its backward-looking nature[1].

Choice of accumulation variables may be advised by insights from the literature on prediction of banking crises by Early Warning Systems (EWS). While theoretical works suggest that a banking crisis could be triggered as a purely self-fulfilling event or through the direct financial exposures that tie banks together or via common exposures to economy wide systematic risk, empirical studies of banking crises' determinants generally neglect the two first channels and focus on the third one. In most EWS works, the variables considered mainly capture macroeconomic factors that could crystallise risks particular to banking systems, namely interest rate, credit, liquidity and market risks. Among these

[1] Gross losses are measuring the part of risk that already materialised while countercyclical capital buffer's objective is to protect banks from risk that may materialise in the future.

factors, special attentions are paid to credit variables (real credit growth, credit to GDP) and asset prices (real estate price, financial assets price)

Credit variables are expected to represent credit risk accumulation. The main argument behind is that during boom episodes, risk assessment by banks deteriorates and loan contracts become less informationally responsive. Banks' managers seem to use biased information sets to make investment decisions, ignoring the potentially high default probabilities that could occur under recessionary states and under-pricing credit risk. Guttentag and Herring (1984) suggest that this results from managers overweighting current positive experience in booms due to various psychological biases. Borio et al. (2001) attribute these suboptimal behavioral responses to difficulties in measuring time series of credit risk and to incentive-based managerial contracts which reward loan volume. Relating to asset prices, they are used as proxies for market risk. Moreover, there seems to exist a close relationship between asset price fluctuations in the property market and bank credit extension. On the one hand, property prices may affect bank lending via various wealth effects. For example, an increase in property prices raises the private sector's borrowing capacity since property is commonly used as collateral. On the other hand, bank lending may affect property prices via various liquidity effects. As an asset price, the property price is determined by the discounted future stream of property returns. An increase in the availability of credit may lower interest rates and then, induces a higher expected return on property.

Empirical studies generally report a positive role of credit variables and asset prices as drivers of crises. From the conclusions of their own empirical analysis, BIS proposes, in the consultative paper, a credit to GDP guide in taking buffer decisions. The paper also notes that this guide should be considered as a useful starting reference point but authorities in each jurisdiction should augment it by other information whenever appropriate.

3 Data Description and Measurement

A. *Original Variables*

Real credit growth: the broadest credit indicator existing in Norway is named C3. It measures the debt of non-financial private sector and municipalities in any form (loans, bond, debt certificates...) from domestic lenders (banks, mortgage companies, finance companies, life and non-life insurance companies, state lending institutions, etc) and also from foreign sources in NOK and foreign currency. C3 is published electronically on Statistics Norway (SSB)'s website. However, since the series on SSB website only dates back to 1986, in this paper, in order to have a series that covers the Nordic recession of 1988/1993 in a sufficiently long time period ahead[2], we sum up two series[3] obtained from database HISTDATA of Norges Bank which represent non-financial enterprises' and households' debt from all credit sources (including external sources). In this way, we have a quarterly series of aggregate credits to private sectors in nominal terms starting on the second quarter of 1975 (1975Q2). We transform this series into real terms by deflation with the CPI[4] and then, compute the 12-month growth. Hence, we get a series of real credit growth from 1976Q2.

Real GDP growth: we obtain a quarterly data on GDP of total Norway and its annual rate of growth (i.e. 12-month growth) in real terms from IMF IFS which covers a period from 1975Q2 to 2009Q3, a longer series than the series of SSB.

Credit-to-GDP ratio: the ratio in each period t is calculated as

$$\mathrm{Ratio}_t = \mathrm{Credit}_t/\mathrm{GDP}_t \times 100\%$$

Both GDP and Credit are in nominal terms and on a quarterly frequency. Given the coverage of the credit and GDP series, we have a series of the credit-to-GDP ratio starting on 1976Q1. Note that here, we use the credit and GDP for Total Norway to compute the ratio. Another alternative is to use the credit and GDP for Mainland Norway only. Our choice comes from the fact that if using Mainland series which date back only to 1986, we cannot generate a conditioning variable that can cover the Nordic crisis (1988). Of course, there exists a question whether Total Norway or Mainland Norway is more relevant. We will try to address this question in the section 5.

Property price: Due to data limitations, in this paper, we focus on residential property prices in Norway. We use as source of information the average price per square meter statistic, produced by Association of Norwegian Real Estate Agents, Association of Real Estate Agency Firms, FINN.no, Econ Pöyry and Norges Bank, which includes quarterly data from 1977Q1 to 2009Q2.

[2] See the explanation of gap computation below for details.

[3] The name of these two series are QUA_KFLTOH (for households) and QUA_KFLLOBE (for non-financial enterprises).

[4] We get a quarterly series of CPI from IMF IFS.

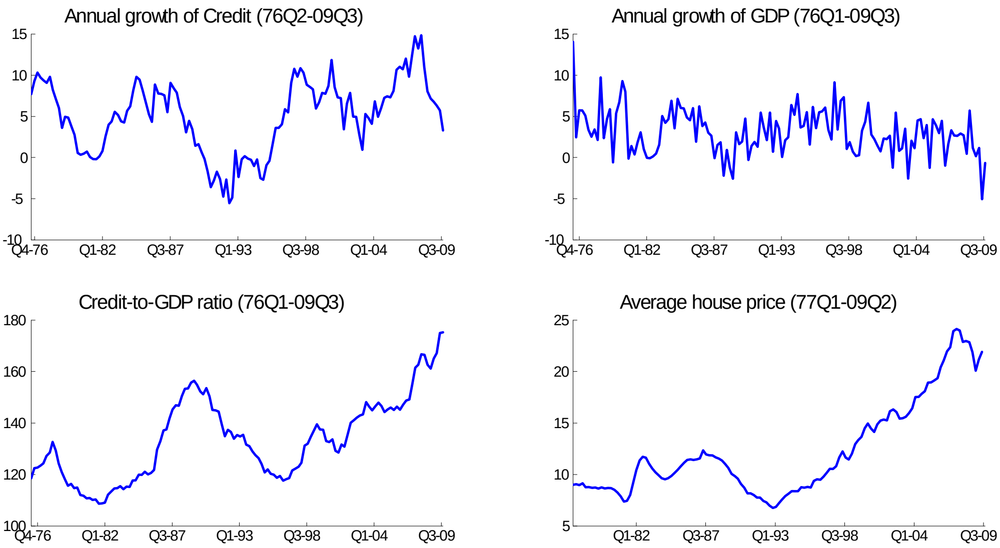


Figure 1: Original Variables

These series are illustrated in figure 1.

B. *Construction of Conditioning Variables*

In order to construct the conditioning variables from the variables above, we compute, for each one, the gap that is defined as deviation from the long-term trend, by using either a HP filter or the simple moving average. By considering the fluctuations of each variable with respect to a long-term trend, we aim at capturing the explanatory power of cumulative processes, rather than growth rates over just one period. The argument behind this approach is that vulnerabilities may build up over an extended period rather than in a single period.

The gaps are estimated so as to incorporate only information that is available at the time the assessments are made. Put differently, the gaps at date t are constructed using only data up until date t. Based on the starting date of our data series, in order to insure the reliability of the gap estimates, we choose to start the first gap calculation on 1985Q1. This choice satisfies two conditions. First, this is sufficiently long before the beginning date of the Nordic crisis (1988). Second, by starting the gap series on 1985Q1, our first gaps are computed from at least 30 observations and so, should be credible. Table 1 summarizes the construction of our gap variables[5].

[5] House price gap is measured as percentage deviation from the trend. Other indicators are measured as percentage point deviation.

Variables	Construction	Coverage of original series	Coverage of gap series
Gap of Credit-to-GDP ratio	One-sided HP filter with $\lambda = 400000$	76Q1 - 09Q3	85Q1 - 09Q3
Gap of average house price per square meter	One-sided HP filter with $\lambda = 400000$	77Q1 - 09Q2	85Q1 - 09Q2
Gap of real credit growth	Simple moving average with 15-year window	76Q2 - 09Q3	85Q1 - 09Q3
Gap of real GDP growth	Simple moving average with 15-year window	76Q1 - 09Q3	85Q1 - 09Q3

Table 1: Construction of Conditioning Variables

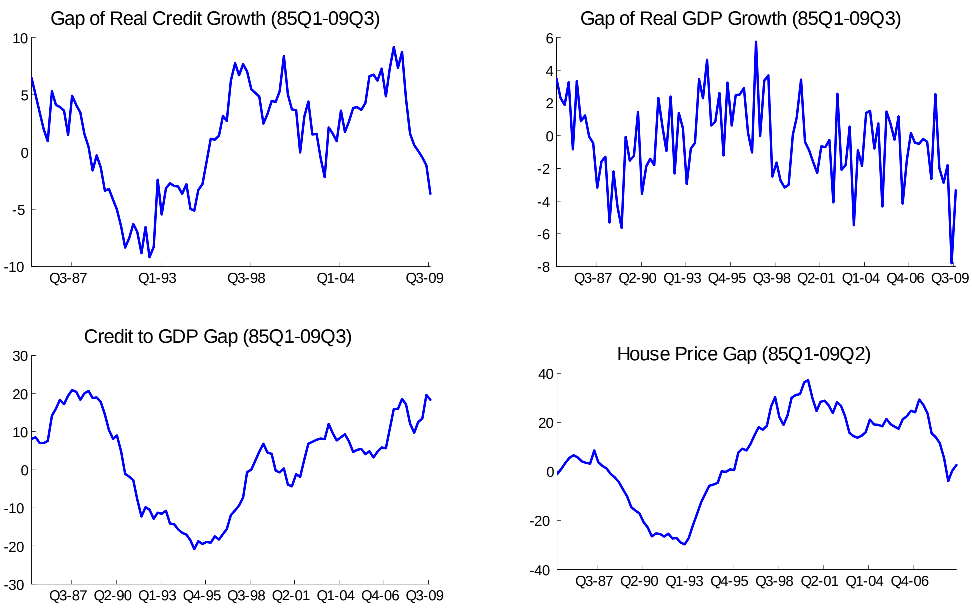


Figure 2: Gap Variables

C. *Preliminary Observations*

A number of observations may be pointed out from figure 2

First, except for GDP growth gap, all three other variables exhibit a quite clear cyclical behavior. They rise smoothly well above the trend before each period of financial distress, suggesting that anomalous behaviors of these variables may reflect the build-up of vulnerabilities inside the financial system. In this sense, they could be good candidates for guiding the accumulation of the capital buffer.

Second, all variables seem to start narrowing way ahead of the emergence of financial strains. Look at, for example, the credit-to-GDP variable: during the Nordic crisis, the gap peaks around the end of 1987 and beginning of 1988, 2 years before the onset of the systemic crisis which is usually dated at the beginning of 1991. The same goes for house price and credit growth. Third, all variables decline too slowly, which implies that they are not able to signal the release phase appropriately neither in terms of timing nor intensity.

Finally, credit growth and house price variables call for accumulating a buffer that is higher in the two periods 2002/2003 and 2007/2009 than in the period 1991/1993. However, the episode 1991/1993 is obviously the most serious crisis in Norway until now. In this aspect, the credit-to-GDP gap seems to have better performance.

4 Signals Approach

In this section, we evaluate, in a more formal way, the performance of conditioning variables by using the signals approach.

A. *General Description*

The signals approach, originally developed to identify turning points in business cycles, was first applied to banking crises by Kaminsky and Reinhart (1999). This approach involves monitoring the evolution of a number of economic variables that tend to exhibit an unusual behavior in the periods preceding a crisis. A warning signal is issued when one of these variables deviates from its "normal" level beyond a certain *threshold* value. A signal is called good signal if it is followed by a crisis within some chosen *signaling horizon*. Otherwise, the signal is said to be false or noise. In fact, there are 4 possible situations:

	Crisis	No Crisis
Signals	A	B
No Signals	C	D

In the above matrix, A is the number of times in which a good signal is issued. B the number of times we observe a wrong signal. C is the number of times where no signal is issued despite the fact that a crisis occurs. Finally, D is the number of times signal is rightly not issued. Obviously, a perfect indicator should produce zero values for C and B.

Different measures can be used to assess the tendency of each individual indicator in issuing good signals. A commonly used criteria is the Noise to Signal Ratio (NSR) defined as $[B/(B+D)]/[A/(A+C)]$. A useful indicator is supposed to have a NSR of less than 1.

Alternatively, an indicator may also be evaluated based on how well it trades off the type 1 error (measured by $C/A+C$) and type 2 error (measured by $B/B+D$).

B. *Empirical Design*

In order to apply the above approach, we make the following choices

First, we consider as representing a banking crisis in Norway two episodes 1988/1993 and 2007/present. There is no unique quantitative criterion for banking crisis in the literature. The crisis is usually identified on the basis of several criteria which may vary from one study to the other. Demirguc-Kunt and Detragiache (1998) used a set of 4 criteria: (1) the proportion of non-performing loans to total banking system assets exceeded 10%, (2) the public bailout cost exceeded 2% of GDP, (3) systemic crisis caused large scale bank nationalization, (4) extensive bank runs were visible or if not, emergency government intervention was visible. Caprio and Klingebiel (1996) defined systemic crisis as an event when "all or most of banking capital is exhausted". Sometimes, expert judgments are referred to determine whether there is systemic crisis. In Norway, although during 2001-2003, the banking system experienced some financial difficulties, the extent of the problem is not sufficiently large. Indeed, during that period, the proportion of non-performing loans peaked at 2,16%, there was no bankruptcy and the capital ratio was still high. Concerning the current financial crisis 2007/present, though the difficulties experienced by Norwegian banks was brought forward through foreign exposures, not from the domestic lending market, given the seriousness of the crisis in the global level, we still include it as a crisis episode. We date the start of this crisis to the third quarter of 2007. For the Nordic crisis of the late 1980s and early 1990s, we consider two possible starting dates: either third quarter of 1988 (specification 1) where we had the first bank failure or fourth quarter of 1990 (specification 2) where we started to observe problems at large commercial banks.

Second, regarding the signaling horizon, we consider multiple horizons. Since it is extremely difficult to predict exactly the timing of a crisis, we will consider the usefulness of indicators in predicting crises within two and three years.

Finally, the definition of warning signals involves some threshold value serving to pick up the abnormal behavior of indicators. Ideally, we should determine the optimal threshold from the data by optimizing some objective function (e.g. minimizing either the NSR or a loss function defined as weighted sum of type 1 and type 2 errors). Since crises are infrequent events, to generate a large number of banking crisis observations, using cross-country data seems to be inevitable. However, the optimal threshold derived from a cross-country analysis is representative for the average country and so, relying on that for calibration in individual countries may lack sufficient degree of confidence. In this paper, we specially look at the Norwegian data and have only 2 crisis observations. Therefore, our objective is not to determine an optimal value for the threshold but to verify whether conditioning variables are informative within a range of threshold values. Note that our gap variables are estimated based on ex-ante information available at each date. As a consequence, the threshold values need to be determined without reference to the entire history of the relevant series. To do this, instead of defining thresholds by a particular percentile of the indicator's own distribution, in line with Borio and Lowe (2002), we simply define thresholds in terms of percentage (or percentage point) gaps.

C. *Empirical results*

Table 2 and 3 report our results for three conditioning variables - i.e. the gaps of the credit growth, of the credit-to-GDP ratio and of the house price - taken individually and using horizons of 2 and 3 years. For each indicator, the tables show a range of relevant threshold values and the associated NSR (table 2) or type 1 and type 2 errors (table 3) for each of these values[6].

In general, all three indicators are able to provide useful information. However, the credit-to-GDP gap is clearly the best, it has lowest noise to signal ratio and a better trade-off between type 1 and type 2 errors. Moreover, the performance of credit-to-GDP gap does not vary much with the threshold values, which is an important observation given the fact that the optimal threshold value should be determined from a cross-country analysis. A threshold value equal to 10 percentage points for the credit-to-GDP gap as proposed in the BIS consultative paper works quite well for Norway.

The performance of Norwegian house prices in predicting crisis is quite bad. The main reason for this poor performance is that while the house price gap could not clearly point

[6] In these tables:

- The specification 1 is consistent with two starting dates for crises, namely 1988Q3 and 2007Q3 while in the specification 2, the first starting date is replaced by 1990Q4.
- The threshold values for the credit to GDP and real credit growth gaps are defined in terms of the deviation in percentage points of the actual series from the trend. For the other gap, the threshold values are expressed as percentage deviations from the trend.

out the vulnerabilities of the banking system before the Nordic crisis, it generated very strong signals prior to the period of 2001 which finally was not materialized in a crisis.

The performance of the indicators improves as the time horizon is lengthened. It is most noticeable for the credit-to-GDP ratio. Furthermore, the performance of each indicator is better in the specification 1 of the 1988-1993 crisis which adopts a softer definition of a crisis than does the specification 2.

D. *Robustness check*

First, a debatable point in the construction of conditioning variables is the choice of smoothing parameter for the HP filter. As it can be seen from the table 1, in the previous analysis, in line with the proposition of BIS, we set the parameter λ equal to 400000 which is a much higher value than the value suggested by the literature on business cycles for quarterly data. This choice is based on the argument that the credit cycles are around 15 years, about two times longer than the business cycles. Thus, to the extent that this assumption does not hold, this could have a bearing on the reliability of the gap measures. We will now address this issue by specially looking at the credit-to-GDP gap in order to see how the performance of this indicator depends on the choice of smoothing parameter.

Figure 3 shows the credit-to-GDP gap for 5 possible values of lambda. A preliminary observation revealed from the figure is that while the gap behaves quite similarly across different lambdas, the precise quantitative value of the gap is strongly affected by the choice of lambda.

Table 4 compares our signals-approach's results for the credit-to-GDP gap using different lambdas. For simplicity, we only report the results in the case of three years horizon and specification 1. We see that although for any value of lambda, the credit-to-GDP gap is always a useful indicator, the performance of this indicator improves as the value of smoothing parameter increases.

Second, relating to the bad performance of house prices, note that our house price data starts in 1977 and that during the period 1977 - 1985, because of deregulation process, the house prices grew very fast. As a consequence, if using a one-sided HP filter, the gap estimate for the episode before the Nordic crisis could be too small. In order to overcome this problem, we here deviate from the real time principle and calculate the house price

A. 3 years horizon & Specification 1

Credit to GDP gap		Credit gap		House price gap	
threshold	NSR	threshold	NSR	threshold	NSR
8	.275	2	.435	10	.898
9	.101	3	.402	12	.857
10	.032	4	.450	14	.816
11	.034	5	.541	16	.694
12	.034	6	.361	18	.692
13	0	7	.361	20	.857
14	0	8	.361	22	1.08
15	0	9	0	24	1.26

B. 3 years horizon & Specification 2

Credit to GDP gap		Credit gap		House price gap	
threshold	NSR	threshold	NSR	threshold	NSR
8	.400	2	.756	10	.898
9	.276	3	.732	12	.857
10	.229	4	.695	14	.816
11	.275	5	.670	16	.694
12	.275	6	.361	18	.692
13	.229	7	.361	20	.857
14	.226	8	.361	22	1.08
15	.209	9	0	24	1.26

C. 2 years horizon & Specification 1

Credit to GDP gap		Credit gap		House price gap	
threshold	NSR	threshold	NSR	threshold	NSR
8	.204	2	.470	10	.909
9	.089	3	.410	12	.871
10	.043	4	.322	14	.835
11	.046	5	.417	16	.725
12	.046	6	.225	18	.759
13	.022	7	.225	20	.642
14	.022	8	.225	22	.675
15	0	9	0	24	.787

D. 2 years horizon & Specification 2

Credit to GDP gap		Credit gap		House price gap	
threshold	NSR	threshold	NSR	threshold	NSR
8	.443	2	.936	10	.909
9	.356	3	.835	12	.871
10	.334	4	.506	14	.835
11	.445	5	.417	16	.725
12	.445	6	.225	18	.759
13	.394	7	.225	20	.642
14	.389	8	.225	22	.675
15	.420	9	0	24	.787

Table 2: Performance of Indicators

A. 3 years horizon & Specification 1

Credit to GDP gap			Credit gap			House price gap		
threshold	Type 1	Type 2	threshold	Type 1	Type 2	threshold	Type 1	Type 2
8	50	13	2	19	35	10	50	45
9	50	5	3	23	31	12	50	43
10	50	2	4	50	22	14	50	41
11	54	2	5	69	17	16	50	35
12	54	2	6	73	10	18	54	32
13	54	0	7	85	5	20	69	26
14	54	0	8	96	1	22	77	25
15	58	0	9	96	0	24	85	19

B. 3 years horizon & Specification 2

Credit to GDP gap			Credit gap			House price gap		
threshold	Type 1	Type 2	threshold	Type 1	Type 2	threshold	Type 1	Type 2
8	46	21	2	42	44	10	50	45
9	50	14	3	46	39	12	50	43
10	54	11	4	61	27	14	50	41
11	61	11	5	73	18	16	50	35
12	61	11	6	73	10	18	54	32
13	61	9	7	85	5	20	69	26
14	61	9	8	96	1	22	77	25
15	65	7	9	96	0	24	85	19

C. 2 years horizon & Specification 1

Credit to GDP gap			Credit gap			House price gap		
threshold	Type 1	Type 2	threshold	Type 1	Type 2	threshold	Type 1	Type 2
8	33	14	2	17	39	10	50	45
9	33	6	3	17	34	12	50	43
10	33	3	4	33	21	14	50	42
11	39	3	5	61	16	16	50	36
12	39	3	6	61	9	18	55	34
13	39	1	7	78	5	20	61	25
14	39	1	8	94	1	22	67	22
15	39	0	9	94	0	24	78	17

D. 2 years horizon & Specification 2

Credit to GDP gap			Credit gap			House price gap		
threshold	Type 1	Type 2	threshold	Type 1	Type 2	threshold	Type 1	Type 2
8	44	25	2	50	47	10	50	45
9	50	18	3	50	42	12	50	43
10	55	15	4	50	25	14	50	42
11	67	15	5	61	16	16	50	36
12	67	15	6	61	9	18	55	34
13	67	13	7	78	5	20	61	25
14	67	13	8	94	1	22	67	22
15	72	12	9	94	0	24	78	17

Table 3: Performance of Indicators

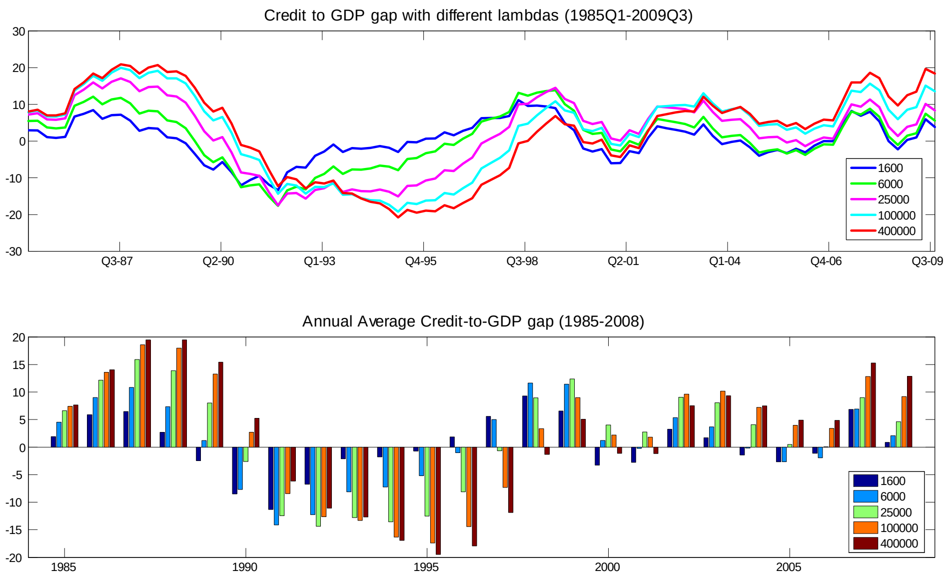


Figure 3: Credit to GDP gap with different lambdas

Credit to GDP gap
(3 years horizon & Specification 1)

$\lambda = 1600$		$\lambda = 6000$		$\lambda = 25000$		$\lambda = 100000$		$\lambda = 400000$	
threshold	NSR	threshold	NSR	threshold	NSR	threshold	NSR	threshold	NSR
2	.608	3	.517	8	.393	8	.459	8	.275
3	.471	4	.582	9	.323	9	.338	9	.101
4	.408	5	.549	10	.267	10	.10	10	.032
5	.371	6	.371	11	.185	11	.033	11	.034
6	.406	7	.244	12	.073	12	.033	12	.034
7	.361	8	.252	13	.079	13	.032	13	0
8	.89	9	.305	14	.044	14	0	14	0
9	inf	10	.356	15	0	15	0	15	0

Table 4: Performance of Credit to GDP gap with different lambdas

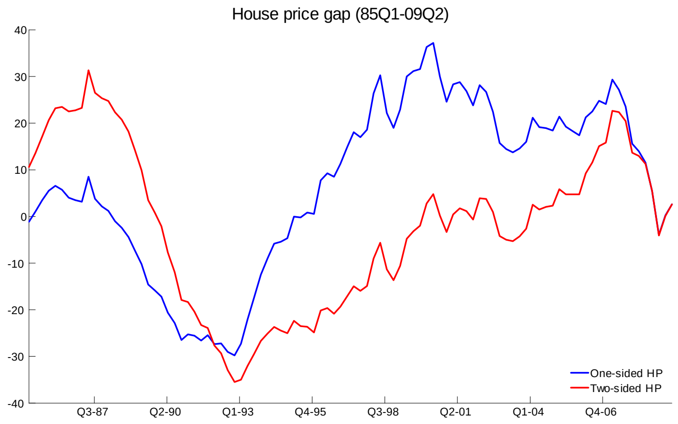


Figure 4: One-sided HP vs. Two-sided HP

gap by using two-sided HP filter. As figure 4 shows, in contrast with the case of one-sided HP filter, with the two-sided HP filter, the house price gap generates, during the period prior to the Nordic crisis, a signal that is much stronger than during two other periods of financial distress (2002/2003 and 2007/2009), which is clearly a better reflection of the reality. From table 5 where we present the signals approach result of the house price gap estimated by two-sided HP filter, we also see that the performance of the house price gap is now much better.

House price gap using two-sided HP
(3 years horizon & Specification 1)

threshold	NSR	Type 1	Type 2
10	0.04	26	3
12	0.02	30	1
14	0	30	0
16	0	38	0
18	0	42	0
20	0	42	0
22	0	53	0
24	0	84	0

Table 5: Performance of House price gap using two-sided HP

5 Bank risk index

In the previous section, we assess the accuracy of different conditioning variables based on their ability in signaling a financial crisis. The drawback of this approach resides in the uncertainty surrounding the identification of a crisis, as Segoviano Basurto, Goodhart and Hofmann (2006) noted *"The exact timing, duration, and intensity of a crisis are all measured with uncertainty. Often crises may be averted by preventative prior action. Is there, therefore, any bias resulting from the study of cases where crises were not averted, while no attention has been paid when crises were averted? Study of a particular crisis on its own runs the risk of putting aside the evidence from noncrisis years".*

Hence, as a complementary, in this section, we evaluate the performance of conditioning variables using another benchmark, namely the risk index for Norwegian banks. Precisely, this risk index is the default probability for individual bank estimated from a logit model[7]. The risk index has been used by Norges Bank since 1989 to identify potential problem banks.

We have data on the risk index from the second quarter of 1991. However, before 1994, the risk index was not specifically designed from Norwegian data but based on the surveillance system of the Federal Reserve. Moreover, during the period 1991-1993, we were at the middle of the most serious crisis in Norway, which should have important effects on the banks' default probability. For these reasons, we exclude three years 1991, 1992, 1993 from consideration.

In order to have a picture of the health of the banking system in aggregate, we calculate the weighted average default probability of ten largest banks in total assets[8]. This measure seems to be better in identifying financial cycles than other measures such as median or percentile (as we see in the figure 5).

We use a very simple methodology to examine the performance of conditioning variables. That is, we compute their correlation with the time series of the weighted average default probability of 10 largest banks.

A number of points emerge from the correlation estimates given in Table 6

- Consistent with the conclusion obtained from the signals approach, the credit to GDP gap has the best performance. It exhibits a significantly positive relationship with the vulnerability of the Norwegian banking system.

[7] See Berg and Hexeberg (1994) and Andersen (2008) for more details. Note that this default probability is not the *actual* default probability of banks but the *model - implied* probability of failure for banks. Hence, the credibility of this benchmark will depend on the accuracy of the logit model used for the estimation.

[8] During the computation process, we observe, on the fourth quarter of 1996, a sudden increase of the weighted average default probability, which is due to the presence of the bank J.P.Morgan Europe Limited Norw among 10 largest banks and its default probability of 99,23%. However, this seems to be a very temporary event: this bank' total assets increase from 9120 MNOK (96Q3) to 21067 MNOK (96Q4) and then, decrease to 13179 MNOK (97Q1). Hence, we decide to exclude this bank from the calculation of the weighted average of 1996Q4.

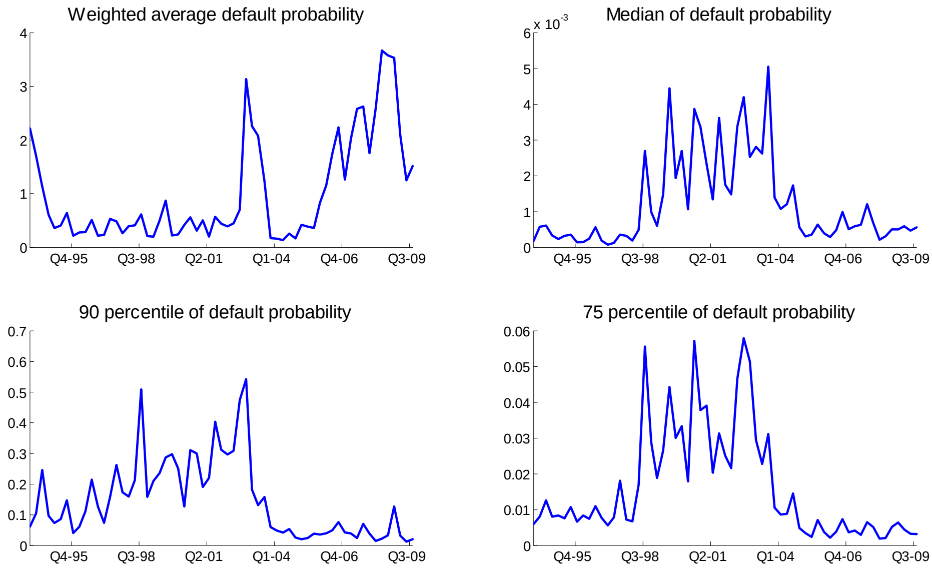


Figure 5: Risk index of Norwegian Banks (94Q1 - 09Q3)

- The performance of two other variables is deceiving. Their correlation with the weighted average default probability even moves in the wrong direction as indicated by the negative sign.
- The performance seems to be improved when a lag is introduced. Moreover, the house price variable needs a longer lag than the credit variables.

A robustness check for the performance of the credit to GDP gap with different lambdas produces the same result as the previous approach (see Table 7)

Variables	Correlation with the weighted average default probability
Credit to GDP gap	0.4593
Credit to GDP gap lagged by 1 quarter	0.4705
Credit to GDP gap lagged by 4 quarter	0.4815
Credit growth gap	-0.0849
Credit growth gap lagged by 1 quarter	0.0286
Credit growth gap lagged by 4 quarter	0.3530
House price gap	-0.2796
House price gap lagged by 1 quarter	-0.1487
House price gap lagged by 4 quarter	0.0978

Table 6: Correlation of conditioning variables with banks' risk index

As we noted in the section 3, calculating the credit to GDP ratio by using Total credit and GDP instead of Mainland credit and GDP may be problematic. However, since we

Credit to GDP gap with	Correlation with the weighted average default probability
$\lambda = 1600$	0.0643
$\lambda = 6000$	0.0163
$\lambda = 25000$	0.1485
$\lambda = 100000$	0.3391

Table 7: Robustness check for the Credit to GDP gap

can compute the gap for Mainland variable only from the fourth quarter of 1993, in the section 4, to be able to cover the Nordic crisis, we use the Total variable. But, we will try to compare the usefulness of Mainland variable (vs. Total variable) by looking at their correlation with the banks' risk index. From the table 8 that reports the correlation for Mainland variable[9], we see that the Total variable seems to exhibit better performance.

Variables	Correlation with the weighted average default probability
Credit to GDP Mainland gap	0.3592
Credit to GDP Mainland gap lagged by 1 quarter	0.3567

Table 8: Performance of the gap of Credit to GDP Mainland

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6 Conclusion

The objective of countercyclical prudential capital is to encourage banks to build up buffers in good times that can be drawn down in bad times. In this paper, we provide a detailed analysis of some macro variables that could play the role of conditioning variables to guide the accumulation of the buffer during the good time based on Norwegian data. The analysis shows that the credit to GDP ratio measured as deviation from the trend could be a good indicator for the vulnerability of the Norwegian banking system. The performance of the Norwegian residential property price as drivers of financial crisis is limited due to the quality of available data.

[9] Given the fact that our Mainland gap series starts on the fourth quarter of 1993 and the series of banks' risk index starts on the first quarter of 1994, when taking into account the lag variable, we include only the lag by one quarter.

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