# Empirical Evidence on the Effectiveness of Capital Buffer Release

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**Abstract**

With the new regulatory framework, known as Basel III, policymakers introduced a countercyclical capital buffer. It subjects banks to higher capital requirements in times of credit excess and is released in a financial crisis. This incentivizes banks to extend credit and to buffer losses. Due to its recent introduction, empirical research on its effects are limited. We analyse a unique policy experiment to evaluate the effects of buffer release. In 2006, the Slovenian central bank introduced a temporary deduction item in capital calculation, creating an average capital buffer of 0.8% of risk weighted assets. It was released at the start of the financial crisis in 2008 and is akin to a release of a countercyclical capital buffer. We estimate its impact on bank behaviour. After its release, firms borrowing from banks holding 1 p.p. higher capital buffer received 11 p.p. more in credit. Also we find the impact was greater for healthy firms, and it increased loan-loss provisioning for firms in default.

*JEL Classification Codes:* G01, G21, G28

*Keywords:* countercyclical capital buffer, macroprudential policy, credit, loan loss provisions

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# 1 Introduction

In response to the financial crisis regulators introduced several macroprudential instruments[1]. They are designed to impede the accumulation of systemic risk and to increase a bank's resilience to shocks. One of the key instruments introduced in Basel III is the countercyclical capital buffer (CCyB). In the periods of excessive credit growth and build-up of system-wide risk, banks are required to build a capital buffer (of up to 2.5% of RWA) in the form of Common Equity Tier 1 capital. It is to be released in downturns to "reduce the risk that the supply of credit will be constrained by regulatory capital requirements that could undermine the performance of the real economy and result in additional credit losses in the banking system BCBS (2015)."

Little evidence on the effect of CCyB exists. CCyB was officially introduced in the euro area in January 2016. Only a few member states currently apply a positive CCyB and none has yet released it.[2] For this reason, the effect of a buffer release has not yet been empirically investigated. We analyze the effect of capital buffer release on bank lending and loan loss provisioning by analyzing a unique policy experiment.

Since there is no data on a CCyB release, empirical research relies on models that proxy the effects of CCyB by using changes in capital ratios.[3] This approach could be flawed. First, the capital ratios are slow to adjust. CCyB release is sudden and generates a discontinuous shift in capital ratios. The data used by previous studies does not account for this effect and fails to articulate the real effects of a CCyB release. Most importantly, changes in capital ratios are (to a large extent) endogenous. They are subject to banks' own decisions (say recapitalization). Those may have a different effect on credit supply than a release of CCyB. In contrast, we employ a policy experiment where the release of a prudential filter is exogenous with respect to the Slovenian banking system.

[1]For an overview of macroprudential policy and its tools see BCBS (2010), Arnold et al. (2012), Galati and Moessner (2013), Claessens (2014), Cerutti et al. (2017) and Kahou and Lehar (2017).

[2]In the euro area, Czech Republic and Slovakia set the CCyB to 0.5% in January and August 2017, respectively. Outside the euro area, Sweden set CCyB to 1% in September 2015 (it is now 2%), Norway to 1% in June 2016 and Iceland to 1.25% in November 2017 (for more information see `https://www.esrb.europa.eu/national_policy/ccb`.). Switzerland implemented a sectoral CCyB. It targets residential real estate and is set to 1% since February 2013. It increased to 2% in January 2014. For further details on Switzerland see Basten and Koch (2015). For other countries see `https://www.bis.org/bcbs/ccyb/`.

[3]Akram (2014) uses a VECM model and Gross et al. (2016) a Global VAR. Noss and Toffano (2016) use sign restrictions to identify shocks in past data that match a set of assumed directional responses of other variables to future changes in aggregate bank capital requirements.

Slovenian banks were allowed to release their capital buffer at the start of the financial crisis in 2008q4. In 2006 Slovenian banks adopted International Financial Reporting Standards (IFRS). Under the IFRS, the loan loss provisions were calculated differently than under the approach of the preceding Slovenian Reporting Standards. As a result, banks were allowed to hold less provisions. Being prudent, Bank of Slovenia (BS) required banks to use the difference in the amount of provisions as a deduction item in the calculation of the capital adequacy ratio. The deduction item was called a prudential filter. Due to it, banks held additional capital from 2006q1 to 2008q3. In response to the financial crisis it was abdicated. It amounted to 0.8% of a system's risk-weighted assets and acted like a countercyclical buffer. Banks accumulated capital in good times only to use as a buffer for losses in bad times.

Our identification strategy adopts methodology proposed by Khwaja and Mian (2008). We estimate the difference in firm's credit growth between two (or more) banks with different sizes of a prudential filter. Because we compare a firm's response across banks, firm-specific shocks such as demand or firm risk, are absorbed by firm-fixed effects. Therefore, we control for loan demand and the observed effect that we identify is unbiased and relates only to differences in the loan supply of banks with different capital buffers.

By using loan level[4] data from the Slovenian credit register, we find evidence that a higher prudential filter caused higher loan growth after the release. For the same firm, borrowing from at least two different banks, where the banks differ in capital buffer size, credit growth was 11 p.p. higher in a bank with a 1 p.p. higher capital buffer prior to its release. In addition, the probability of loan increase for a firm was 5.8 p.p. higher with a bank with 1 p.p. higher capital buffer. We also find that lending was directed towards less risky firms. Finally, we test if banks used additional loss absorption capacity to increase provisions for defaulted borrowers. Coverage ratio increased by 8.6 p.p. more in banks with a 1 p.p. higher buffer, for firms that defaulted at the time of buffer release. We find strong empirical evidence on the stabilizing effects of capital buffers.

Our findings complement theoretical and simulation-based models that argue in favour of countercyclical capital buffers. Aikman et al. (2015) use a three period model and Rubio and Carrasco-Gallego (2016) a DSGE model in which CCyB reduces excess credit buildup. Brzoza-Brzezina et al. (2015) employ a DSGE model to show that CCyB mitigates credit imbalances in the build-up phase, however loan-to-value (LTV) restriction is shown to be more effective in this respect. We show that

[4] Firm-bank level data.

CCyB is effective in the release phase where LTV cannot be effective by definition. Tayler and Zilberman (2016) and Gersbach and Rochet (2017) employ a DSGE model to show that CCyB curbs credit cycles. Additional support in this respect is provided by Biu et al. (2017) who apply simulation techniques to show that a higher capital buffer would reduce system-wide losses and therefore increase the resilience of the Australian banking system. Their simulation also shows that banks would limit credit supply in response to higher capital requirements. We in addition analyze how a buffer affects lending and loan loss provisioning in the downturn phase.

Our paper is closest to Jiménez et al. (2017). Jiménez et al. (2017) offer valuable and rich insight from an instrument called dynamic provisions. They use exhaustive loan-level data to show that the release of dynamic provisions increased credit supply in Spain when the crisis hit. To our knowledge, Jiménez et al. (2017) and us are the only two research studies that use a policy experiment to estimate the effects of a CCyB release. An important difference is that the dynamic provisioning follows a formula, so banks can anticipate future releases better than in our experiment, where the release is caused by a crisis, which was unexpected and exogenous for Slovenian banks. In addition, we provide evidence on the interaction of loan loss provisioning and capital buffer, which is an unresearched mechanism of this instrument.

Our findings have several implications for policymakers and regulators. We show that CCyB increases bank lending in a crisis period. This could have a limited effect on the real economy according to some studies (see Peek and Rosengren (2005) and Iosifidi and Kokas (2015)). Banks might have an incentive to lend to borrowers that are close to default to reduce pressure of non-performing borrowers on capital. This is not what we find. Our results show that less risky firms, without delays in repayments, benefited most. This is a desired outcome, as it intensifies the positive effect of a capital buffer release on the real economy. An additional favourable effect is faster recognition of losses by banks. As shown by Beatty and Liao (2011) and Homar and van Wijnbergen (2015), fast recognition of losses and timely bank recapitalisations make crises shorter and less intense. Our findings show that a capital buffer was effective at the beginning of the crisis as banks with higher reserve capital provisioned more.

The paper is structured as follows. In the next section we introduce the prudential filter and macroeconomic environment in Slovenia in the period when it was active. Section 3 presents the methodological approach and data used for the analysis. Section 4 presents the results. Finally, Section 5 concludes the paper.

## 2 Prudential Filter

This section provides insights on the functioning of the prudential filter, which was introduced at the beginning of 2006 and released at the end of 2008, when the crisis hit. We first discuss macroeconomic and banking environment in Slovenia in the period 2007-2010. Then we present the functionality of the prudential filter in more detail.

### 2.1 Macroeconomic and Banking Environment

The period surrounding the buffer release is characterized as a period from high economic and credit growth to a deep recession. After a period of high growth, GDP turned negative in 2008q4 (see Figure 1)[5], exactly at the time when a prudential filter was released. GDP further contracted in 2009, followed by a mild recovery in 2010. The recession severely affected the banking sector. Credit growth quickly declined. It decreased to 0% in 2009. A freeze of the European interbank market, that represented an important source of funding for Slovenian banks, contributed to this. A decrease in economic activity was accompanied by an increase in the share of non-performing loans. This latter became the main problem of Slovenian banks.[6] Concurrently bank profit declined. In 2010 it turned negative and Slovene banks started recording losses. Between 2009-2014, losses amounted to 10% of total pre-crisis assets.

The Bank of Slovenia decided to release the prudential filter in 2008q4. This was the time of the first signs of a banking crisis, triggered by an exogenous shock. A deep contraction of credit growth followed in 2009. It was accompanied by a decrease in economic activity that likely decreased loan demand. Estimation methodology that does not control for a fall in loan demand will lead to a biased estimate because its decrease would attenuate the size of coefficients. Our identification strategy is free from this bias. We employ a loan level differences-in-differences model to control for loan demand (see Section 3.1).

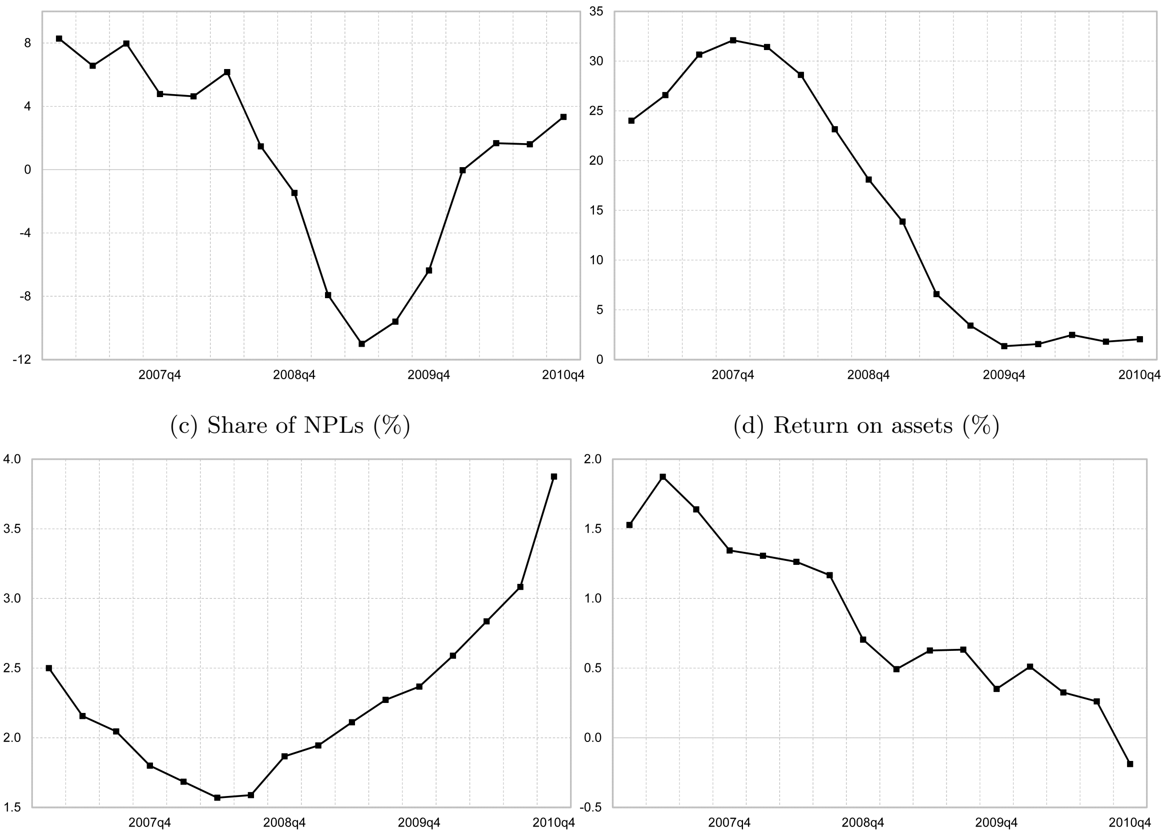
### 2.2 Functioning of Prudential Filter

Following the introduction of International Financial Reporting Standards (IFRS) in 2006, the Bank of Slovenia introduced the prudential filter. The prudential filter implicitly increased regulatory

[5]Banking sector variables are calculated as weighted averages across banks. A bank's weight corresponds to a bank's share in total assets.

[6]In this study we define NPLs as loans to borrowers classified as C, D or E in the five-grade rating scale from A to E.

Figure 1: Macroeconomic and Banking Environment is Slovenia in 2007-2010




(a) GDP growth (% y-o-y)

(b) Credit growth (% y-o-y)

(c) Share of NPLs (%)

(d) Return on assets (%)

Source: Bank of Slovenia, own calculations.

capital requirements, acting as CCyB. These were released in 2008q4. This section describes the nature and regulatory aspect of the prudential filter.

In 2002 the European Parliament and Council adopted a Regulation EC/1606/2002. It required EU banks to traverse from national accounting standards to IFRS by January 2006. The Regulation had a major impact on the Slovenian banking sector. Under the IFRS accounting standards, provisions and impairments are recorded at fair value instead of at historical cost, as was done before 2006 under the Slovenian Accounting Standards.

When a bank gives a loan there is a risk that it will not be re-paid in full. To account for losses banks apply impairments. The difference in the carrying amount of the loan and the recoverable amount results in impairments[7]. They are conventionally expressed in percentages of the carrying amount of loan. A bank records the impaired value of the loan on the assets side of its balance sheet.

[7] This definition is derived from the official definition published in The Official Gazzete of the Republic of Slovenia (2015, No. 50).

On the liabilities side of the bank's balance sheet, impairments reduce the amount of capital. This is because the impaired amount of the loan enters into the bank's income statement as a deduction to the bank's profit, which is subsequently added to the banks capital. The bottom line is that the higher/lower the impairments are the more/less capital a bank needs to hold in order to fulfill the regulatory capital requirements.

Before 2006, provisioning rates were set by the Bank of Slovenia. It set them based on historical data in a conservative manner. Provision and impairment rates applicable before 2006 are presented in Table 1. When the bank issued a loan, it immediately impaired the carrying amount in line with risk buckets presented in Table 1. If a loan was downgraded to a higher risk bucket, the bank had to apply higher provision rate irrespective if the loss has not materialized.

Table 1: Provision and impairment rates valid in Slovenian banking sector before 2006

| Rate | Credit rating | Description |
|---|---|---|
| 1% | A | Official institutions, no overdue, premium collateral |
| 10% | B | Expected to be repaid, overdue under 30 days, |
| 25% | C | Insufficient cash flow, overdue 30-90 days |
| 50% | D | Not expected to repaid in full, overdue 90-360 days |
| 100% | E | Not expected to be repaid, overdue above 360 days |

Source: Provision or impairment rates can be found in The Official Gazzete of the Republic of Slovenia (2005, No. 67a), article 22. Definitions of asset classes can be found in the same document, under article 11.

In 2006, Slovenian banks traversed to IFRS. Under the IFRS the provision and impairment rates were no longer set by the Bank of Slovenia, but were set by banks themselves using fair value approach. Many banks kept the system of assigning provisions based on credit ratings. But, importantly, banks were now free to determine provisioning rates for each risk bucket. They no longer applied those presented in Table 1.

On average, the historical approach imposed higher provision and impairment rates than the fair value approach. Under the fair value approach a bank is required to provision for losses related to materialized events. In contrast, under the historical approach the loan loss provisions are recorded regardless if the losses have materialized or not.

The Bank of Slovenia foresaw that the amount of provisions and impairments will decrease under the IFRS (see Bank of Slovenia (2015)). A substantial decrease of provisions and impairments would increase bank profit at that time, which could be paid out in dividends, making banks less capitalized and riskier.

To prevent capital outflow, the Bank of Slovenia amended rules on credit risk calculation[8] and the regulation on bank capital calculation[9]. The amendments stated that, for regulatory purposes, the banks were required to introduce a (own funds) deduction item[10]. It was named *prudential filter* and was calculated as the difference between provisions and impairments calculated by using the historical approach rates and the provisions and impairments calculated under the fair value approach. This rule applied only to loans and claims that were provisioned collectively under the IFRS. Individually impaired loans, which are to a large extent non-performing loans, were exempt from this calculation, since for these loans the bank thoroughly assesses the expected cash flow and provision accordingly.

Since the prudential filter was deducted from Tier I capital, it forced banks to hold higher capital from 2006q1 to 2008q3. This approximated the effect of a counter-cyclical buffer if it existed at the time.

On several occasions banks requested to abdicate the prudential filter. That would make banks more profitable per unit of capital, but also less resilient to future shocks. The Bank of Slovenia declined their requests and only removed the prudential filter in 2008q4, at the first signs of financial crisis. As a direct impact of the abolishment of the prudential filter, the bank capital adequacy ratio increased, on average by 0.8 percentage points. Sudden increases in bank capitalization implied that banks could use excess capital for either lending or credit loss absorption. This is exactly what the counter-cyclical capital buffer is designed for.

The functioning of the prudential filter is presented in Figure 2. The dashed line shows the amount of the prudential filter, which was about 0.8% of RWA before the release and zero afterwards. The capital adequacy ratio (solid line in Figure 2) displays a mirrored picture. It increased when the prudential filter was released. The prudential filter increased capital requirements during an expansionary period and alleviated them in time of crisis.

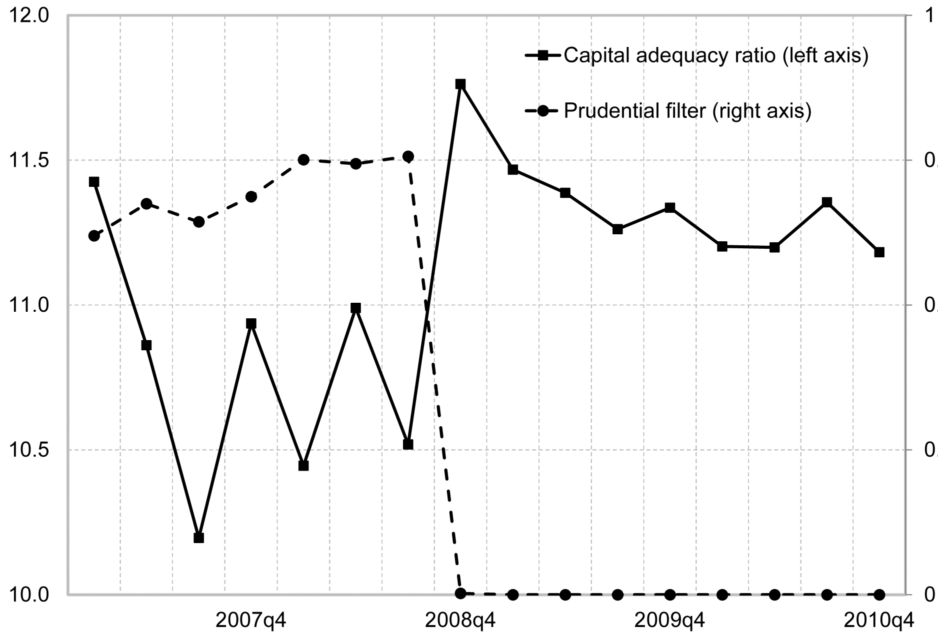
Figure 3 shows the capital adequacy ratio by banks before and after the release. The prudential filter caused an increased in the CAR for all banks except one. Note the difference between the dashed and solid line in Figure 3. It does not arise only due to a prudential filter release. There might have been other factors influencing the change in the CAR between 2008q3 and 2008q4, say recapitalization or realization of losses. This explains a decrease in the CAR for the one bank, which

[8] See The Official Gazzete of the Republic of Slovenia (2005, No. 67a).

[9] See The Official Gazzete of the Republic of Slovenia (2005, No. 67b).

[10] Own funds is a broader definition of capital that also includes Tier I capital and secondary capital.

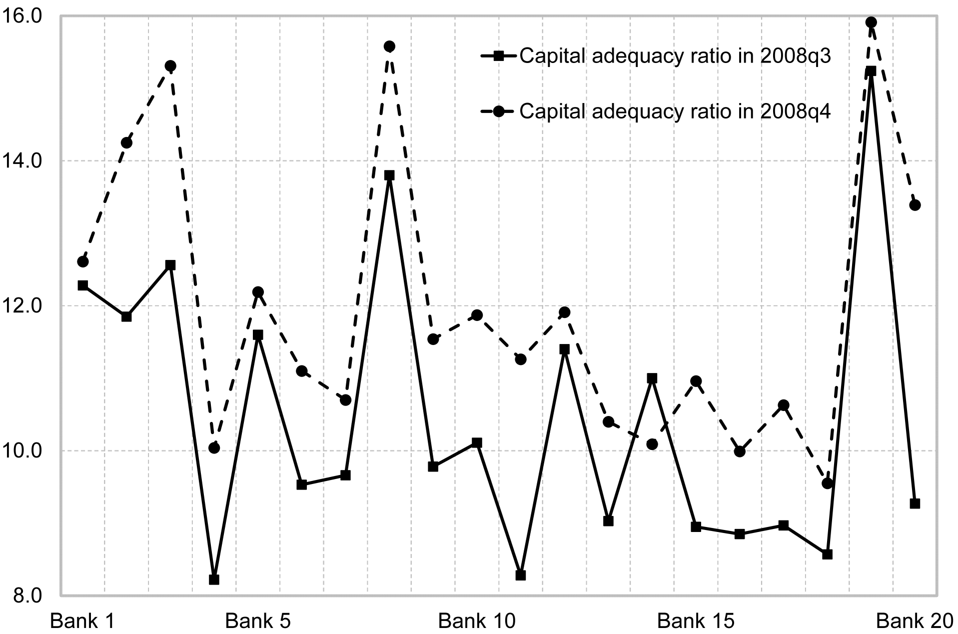
Figure 2: Weighted Mean of CAR and Prudential Filter in % of RWA, 2007-2010




Source: Bank of Slovenia, own calculations.

could not arise due to the prudential filter release. The prudential filter can only increase capital available to a bank.

Figure 3: CAR before the release (2008q3) and after it (2008q4), across banks

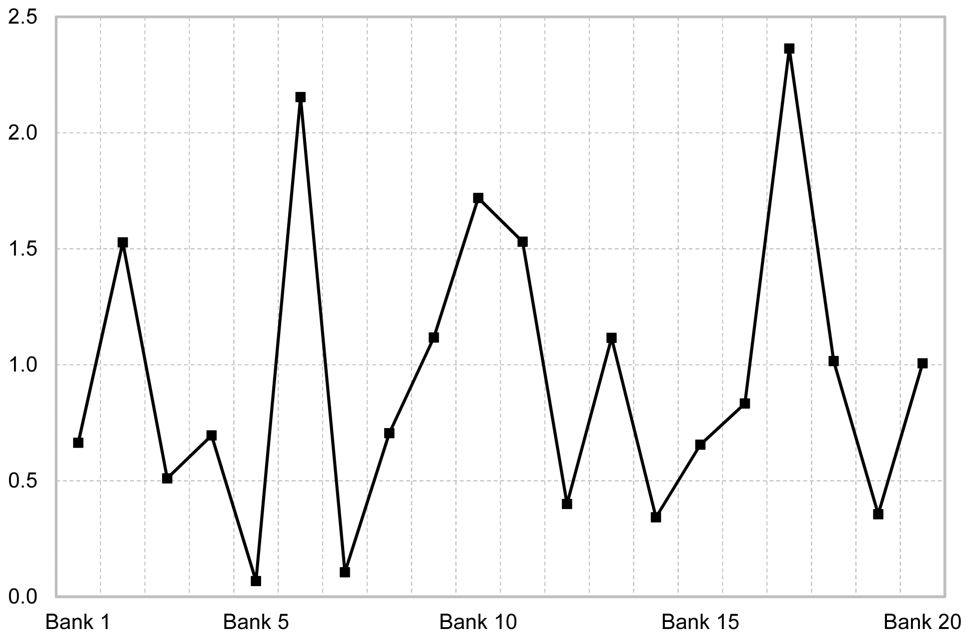



Source: Bank of Slovenia, own calculations.

Pure effects of the prudential filter release on capital adequacy ratio is depicted in Figure 4. It shows the amount of the prudential filter in 2008q3, just before it was released, in percent of

RWA. This is our main policy variable. We use it in a loan level model to test if banks with a higher amount of prudential filter lent and provisioned by more at the beginning of the crisis. Our identification strategy (described in Section 3.1) demands that prudential filter varies across banks. This enables us to estimate the effect of a 1 p.p. increase in capital buffer on bank lending, while controlling for loan demand[11]. Fortunately, it does vary across banks. Nine banks had a prudential filter that was above 1% of RWA. Nine banks had values within a band of 0.3-1% and two banks held a prudential filter that was close to 0%. These amounts translated to an increase in capital adequacy at the time of prudential filter release.

Figure 4: Prudential Filter in 2008q3 in % of RWA, across banks




Source: Bank of Slovenia, own calculations.

There is a conceptual difference between the prudential filter and the CCyB. Under the CCyB the rate of additional capital is same for all banks (up to 2.5% of RWA). On the other hand, prudential filter was bank specific. It ranged from close to 0% of RWA to 2.4% of RWA. The fact that the prudential filter varied facilitates our analysis. For this reason we estimate the average effect of a 1 p.p. increase in the capital buffer. Note also that the CCyB is applied by increasing the minimum capital requirement whereas prudential filter decreased the accounting value of capital that entered the calculation of capital adequacy ratio. Regardless, in practice they both increase

[11] If each bank-firm pair had the same amount of prudential filter we could not exploit the differences-in-differences approach. The difference would always be zero. If we could not exploit the differences-in-differences approach we could not control for loan demand.

capital available to banks at the time of capital release.

# 3 Methodology

We now present the identification strategy and data used to estimate the effect of the capital buffer release on bank lending and loan loss provisioning.

## 3.1 Identification Strategy

In this section we describe the identification strategy employed in the loan level model. Its key advantage is that it controls for loan demand and thereby yields unbiased and consistent estimates of coefficients. Methodology used in this section was put forward by Khwaja and Mian (2008). It was further adopted by Jiménez et al. (2010), Jiménez et al. (2017), Bonaccorsi di Patti and Sette (2016), Behn et al. (2016) and others.

Khwaja and Mian (2008) use a clever estimation technique that allows one to control for loan demand. It is an unobserved variable[12]. This implies that any model explaining credit growth is missing a key control variable. If this variable is correlated with other regressors, the coefficients are biased and inconsistent. The extent of bias depends on the degree of its correlation with the variable that we are vested in. A possible way of controlling for loan demand is to introduce a proxy for loan demand, such as real GDP or investment. But unfortunately, the degree of bias will remain unknown.

Khwaja and Mian (2008) bypass this issue by exploiting loan level data. In their setting, loan level data are data on borrowers with (at least) two banking relations. The idea is simple. If in a given period the borrower's loan demand is constant over two banks, then we can introduce a borrower specific dummy that controls for loan demand. An analogous approach is used in a fixed effects model by means of transforming the data over the time dimension[13]. The next few

[12]Only in rare instances is the researcher endowed with loan applications data which are an excellent proxy for loan demand. See for example Jiménez et al. (2012).

[13]By employing either a dummy variable estimator, within, between or the fixed effects transformation. Note the subtle difference between the fixed effects estimator and the Khwaja and Mian (2008) difference-in-difference estimator. The fixed effects estimator exploits the fact that the fixed effects are constant over time. With at least two time periods of observations they can be controlled for using a dummy for each borrower or by means of data transformation. This works similarly also in our case, the only difference being that instead of time the second dimension that determines the panel are banks, since time is fixed to only one period.

paragraphs present a simplified example that explains the idea originally put forward by Khwaja and Mian (2008).

Suppose that we have $N$ borrowers with at least two banking relations in a given time period[14]:

$$y_{ij} = \beta X_{ij} + \eta_i + \epsilon_{ij} \tag{1}$$

Where $y_{ij}$ stands for borrower $i$'s loan growth (where $i = 1...N$) in bank $j$ (where $j = 1...M$) in specific time period around the filter release. The period is defined in Section 3.2. $X_{ij}$ represents a $K \times 1$ vector of policy and control variables that we don't specify further at this point. $\eta_i$ represents firm-level effects that can not be observed by the researcher. The key firm-level unobserved effect in our model is loan demand. Suppose we now add to eq. (1) a dummy variable that takes the value of 1 for individual $i$ and zero elsewhere[15]. Because $\eta_i$ is invariant between banks ($j = 1...M$), it will be absorbed by the dummy variable:

$$y_{ij} = \beta X_{ij} + D_i + \epsilon_{ij} \tag{2}$$

Since $D_i$ is equal to one for all banks it absorbs firm demand and all other firm characteristics. The observed effect can thus be fully attributed to the differences between banks. In our case this means that the estimated effect of prudential filter release on credit growth, presented in the next section, can be attributed to differences in banks loan supply related to different levels of prudential filter.

We use the same approach to estimate the effect of a buffer release on bank loan loss provisioning. The dependent variable in that case is a change in the coverage ratio realized by bank $j$ for firm $i$. Two key factors determining the rate of provisioning are firm riskiness and the amount of collateral. While both variables can in general be observed, our loan level methodology is still advantageous. It captures all firm-level effects, including riskiness and availability of collateral. We address other potential firm-bank specific issues in Section 4.

[14]This is a reduced form model. Khwaja and Mian (2008) derived it from a simplified theoretical model.

[15]The estimator of such model is called the least squares dummy variable estimator. If the number of borrower's ($N$) is large one can use transformations of the data (like for instance within transformation) that cause the fixed effects to drop from equation 1.

### 3.2 Data

We use data from the credit register of the Bank of Slovenia. It contains multiple observations for each borrower in each time period. This is necessary for our identification methodology described in the previous section. Loans on a borrower level are available only for firms. Households loans are reported only cumulatively across risk buckets and can not be used with our loan level model. By considering only corporate loans we still capture majority of total loan volume to private non-financial sector. Loans to households represented only 23% of credit to private non-financial sector in 2008.[16]

The first important step in data preparation is to select an appropriate period to be used in credit growth calculation. Our baseline period is credit growth in the period between one quarter before prudential filter release (2008q3) and three quarters after the release (2009q3). One could argue that this selection is rather subjective. We also estimate the model on horizons from 1 to 4 quarters after the release and report on those results.

We exclude firms with missing values. For identification purposes we restrict our sample to firms that are indebted to at least two banks. After imposing this restriction we are left with 7,882 firms. They account for 22.3% of all the firms that were in the same period indebted to at least one bank. Admittedly, this share is low, however, their total loan amount is equal to 84.2% of loans. Thus the data is representative and covers a large share of the total amount of loan to firms. Firms indebted to multiple banks are typically larger and hold bigger loan amounts. Next, for estimating the effect of buffer release on lending, we restrict our sample to performing firms only. We exclude the non-performing firms because accounting rules dictate that non-paid interest on NPLs have to be added to the amount of non-performing loans. Increase of the the loan amount is caused by accounting regulation and could be spuriously correlated with our regressors. Lastly, to eliminate outliers, we exclude firms of the 1st and 100th percentile of the distribution of our dependent variables.

In estimating the effect on loan loss provisioning we focus on firms that are either in default or have difficulties in repaying the loan. Only these need to be provisioned extensively and account for

[16] We also performed aggregate analysis where also loans to households were included. We estimated the bank level dynamic panel-data model where the dependent variable is loan growth to firms and households. The results are in line with the findings presented in Section 4. The estimated effect of buffer release on bank lending is however lower, which can be attributed to the lack of control for loan demand in the bank level model, different sample and different estimation methodology. The results are available upon request. We do not report on them because of the potential presence of omitted variable bias.

the majority of loan loss reserves. Including the performing firms we would find a much smaller or maybe even no effect on provisions. The reason being that there is no need to provision additionally for firms that repay their loan regularly. This follows from the IFRS incurred loss provisioning model. Similarly as in the case of loan growth analysis we eliminate outliers.

Table 2 shows summary statistics for the variables included in the model. Credit growth is calculated as a percentage growth comparing one quarter before release and three quarters after the buffer release (2008q3 to 2009q3). Mean credit growth is 15%. Loan increase is a dummy variable equal to 1 if firm $i$'s loan amount increased in bank $j$ in the period 2008q3-2009q3. 34% of the firms increased their indebtedness after the release. The second variable of interest is change in coverage ratio. It has a mean equal to 11.3 p.p.[17] It is calculated only for the non-performing firms. All policy and control variables are included in the model at their values in 2008q3, i.e. just before the release. The average value of our main policy variable, the prudential filter, was 0.72%[18] in 2008q3. Bank size is measured by total assets. Its average value in 2008q3 was about EUR 5 bln. Average capital adequacy ratio, share of non-performing loans and y-o-y bank credit growth before the filter release were 10.1%, 2.7% and 25.7%, respectively.

Table 2: Summary Statistics

| Variable | Unit | Mean | Std. Dev. | Min | Max | Obs |
|---|---|---|---|---|---|---|
| Loan growth | % | 14.79 | 105.36 | -90.47 | 1166.67 | 11984 |
| Loan increase | 0/1 | 0.34 | 0.47 | 0 | 1 | 11984 |
| Change in coverage ratio | pp | 11.30 | 28.46 | -81.70 | 92.86 | 1429 |
| Prudential filter | % | 0.72 | 0.36 | 0.07 | 1.53 | 11043 |
| Total assets | EUR bln | 5.16 | 5.33 | 0.02 | 15.10 | 11984 |
| Capital adequacy ratio | % | 10.07 | 1.60 | 8.22 | 15.23 | 11984 |
| Share of NPLs | % | 2.66 | 1.20 | 0.05 | 4.77 | 11984 |
| Bank credit growth | % y-o-y | 25.72 | 13.73 | 9.80 | 54.08 | 11984 |

Source: Bank of Slovenia, own calculations.
*Notes*: Loan growth is calculated for the period 2008q3-2009q3. Credit increase is a dummy variable equal to 1 if firm $i$ loan amount increased in bank $j$ in period 2008q3-2009q3. Prudential filter, total assets, capital adequacy ratio, share of NPLs and Bank credit growth are reported at their values from 2008q3, just before the release took place. Change in coverage ratio is calculated for defaulted firms, whereas all other statistics are reported for performing part of the sample.

# 4 Results

This section presents the results. We investigate if banks with a higher amount of a prudential filter and a higher capital adequacy lent more at the beginning of the crisis. Next, we verify the nature

[17] Change in coverage ratio is calculated as $\Delta CR_{ij} = \frac{Provisions_{ij,2009q3}}{Loans_{ij,2009q3}} - \frac{Provisions_{ij,2008q3}}{Loans_{ij,2008q3}}$.

[18] Note that this is a non-weighted average, calculated on a limited sample.

of firms the additional lending was directed to. Lastly, we verify if banks used spare loss-absorption capacity, that occurred with capital release, to provision more for bad loans. By answering these questions, we can test whether the policy of a capital buffer release in bad times is effective and if it serves its main goals.

Table 3 shows the effect of buffer release on bank lending.[19] Dependent variable is firm's $i$ credit growth on a loan taken with bank $j$ in period 2008q3-2009q3. We control for firm specific demand with firm-fixed effects and include several controls for other influences. Model (1) in Table 3 shows our baseline results. We find that for the same firm, borrowing from at least two different banks that differ in the size of prudential filter, credit growth was 11.1 p.p. higher if the bank had a 1 p.p. higher capital buffer. By using standard errors clustered at the bank level, this coefficient is statistically significant at conventional levels. This implies that a capital buffer release indeed increased bank lending.

Table 3: The Effect of Capital Buffer Release on Bank Lending

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Prudential filter | 0.111** | 0.118** | 0.124** | 0.130** |
| Capital adequacy ratio | 0.016 | 0.020* | 0.017 | 0.018 |
| Share of NPL | 0.024* | 0.032* | 0.024 | 0.024 |
| Total assets | -0.000* | -0.000 | -0.000* | -0.000* |
| Credit growth | | 0.131 | | |
| Prudential filter*$I(Overdue > 0)$ | | | -0.212** | |
| Prudential filter*Rating | | | | -0.048 |
| Constant | -0.124 | 0.231 | -0.134 | -0.145 |
| Firm FE | Yes | Yes | Yes | Yes |
| Number of observations | 11,043 | 11,043 | 11,043 | 11,043 |

Source: Bank of Slovenia, own calculations.
*Notes*: The table reports the estimation results for loan level differences-in-differences model. Dependent variable in all the equations is firm $i$ loan growth in bank $j$ in period 2008q3-2009q3 (10% is expressed as 0.1). Prudential filter is its amount in 2008q3 (just before the release), expressed in percent of RWA. Capital adequacy ratio, share of NPL and bank total assets are taken from 2008q3. Credit growth is bank specific credit growth in year before prudential filter release. $I(Overdue > 0)$ is an indicator equal one if firm $i$ repays the loan to bank $j$ with overdue higher than zero days. Rating is a credit rating assigned by bank $j$ to firm $i$ and takes values from 0 (rating A) to 4 (rating E). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We now extend our baseline model with a bank's credit growth in the year prior to prudential filter release. If banks that held a higher amount of prudential filter are the banks that lent more before the capital release then the identified effect could be incorrectly attributed to the prudential

[19] As explained before, we focus on performing firms. We verified the results by extending the sample with firms

filter release. It might only reflect a higher credit growth of banks that incidentally held a high amount of prudential filter. As shown in model (2) in Table 3 this is not the case. Even when controlling for a bank's credit growth, the prudential filter displays a positive and statistically significant effect. In addition, the effect of bank credit growth before the release of capital is found insignificant.

Our next set of results investigates which firms benefited from the positive effect of the filter release. Note that this was the period when the crisis began and non-performing loans started to accumulate in bank balance sheets. Banks may engage in the evergreening of loans to riskier firms. They do this to reduce the pressure of loan-loss provisions on capital. This phenomenon is well documented by Peek and Rosengren (2005). If the capital buffer amplifies this effect that would be undesirable.

To verify this, we interact prudential filter with two variables that measure firm riskiness. The delay with which firm $i$ repays debt to bank $j$ is an indicator of risk. Model (3) in Table 3 shows this result. The interaction term is negative. In addition, the sum of the coefficients for a prudential filter and the interaction term is also negative. This implies that the positive effect of the prudential filter release is not only reduced for borrowers that have difficulties with loan repayment, but is even negative. The credit rating assigned by bank $j$ to firm $i$ is our second measure of risk. It takes a value from zero (rating A) to four (rating E). The coefficient on the interaction term is negative, though it is not statistically significant (exact p-value is equal to 0.153). Overall, we conclude that solid and safe firms gain the most from a capital buffer release. This is a desirable outcome for policy makers.

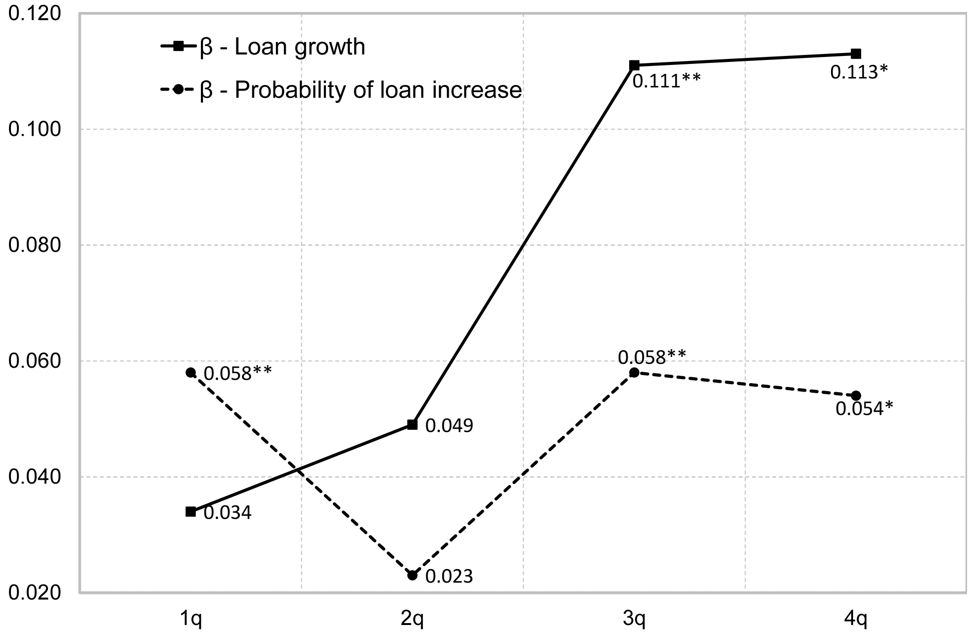
The results presented indicate a possible impact of a capital buffer release on loan growth for a specific time horizon, 2008q3-2009q3. To verify the robustness of this result we present regression results based on different periods. So far, we have used 2008q3 as a cut-off date before the prudential filter is released. We would like to stay as close as possible to the time of the buffer release so we do not contaminate the dependent variable with other effects. For the same reason we also don't look any further beyond 1 year after the release.

Figure 5 presents the results for horizons that span from 1 to 4 quarters after the release. The effect of capital release on loan growth peaked in the third quarter after the release. Importantly, the estimated coefficient is positive in all the cases. It is, however, statistically significant only for

that eventually defaulted. The results were similar and are available upon request.

the third and fourth quarter after the release. This is to some extent expected, since banks typically need some time to re-allocate spare capital.

Figure 5: Coefficient for loan growth and for the probability of a loan increase on one- to four-quarter horizon after the release




Source: Bank of Slovenia, own calculations.
Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also estimate the probability of a loan increase based on the release of a prudential filter. The dependent variable is equal to 1 if firm $i$'s amount of loan borrowed from bank $j$ has increased in the period. We use the same time horizon as in our benchmark regression. The advantage of this approach is that the estimated effects are not driven by outliers, which are, despite certain exclusions, still quite high. The results are presented in Figure 5. Comparable to credit growth, we find that release of the capital buffer increases the probability of a loan growth. We find that a firm had a 5.8 p.p. higher probability of a loan increase with a bank that held a 1 p.p. higher capital buffer.

We now explore the effect of capital release on bank loan loss provisioning. Due to a filter release banks obtained spare capital that increased their loss absorption capacity. A study by Brezigar-Masten et al. (2015) shows that banks intentionally underestimated credit risk in response to an increase in non-performing loans. We test if banks with higher capital buffers provisioned more, thereby ameliorating underestimation of credit risk.

Results are presented in Table 4. The dependent variable is the change in the coverage ratio for each observation between 2008q3 and 2009q3. We control for firm fixed effects. We focus on firms that are either in default or are in overdue. We present three different sets of results differing in firm's overdue.

Table 4: The Effect of Capital Buffer Release on Bank Loan Loss Provisionig

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\text{Overdue}_{2009q3} > 0$ | $\text{Overdue}_{2009q3} > 90$ | $\text{Overdue}_{2008q3} = 0$, $\text{Overdue}_{2009q3} > 0$ |
| Prudential filter | 0.084** | 0.077** | 0.086* |
| Capital adequacy ratio | 0.001 | 0.012* | 0.021 |
| Share of NPL | -0.014 | -0.007 | -0.014 |
| Total assets | 0.000 | 0.000 | 0.000 |
| Overdue | 0.000 | 0.000 | 0.001*** |
| Constant | -0.026 | 0.006 | -0.235 |
| Firm FE | Yes | Yes | Yes |
| Number of observations | 2,032 | 1,337 | 856 |

Source: Bank of Slovenia, own calculations.
*Notes*: The table reports the estimation results for the loan-level differences-in-differences model. The dependent variable in all the equations is the change in loan loss provisioning ratio between 2008q3 and 2009q3. Model is estimated for three subsamples: (1) and (2) includes firms that had overdue higher than 0 and 90 days, respectively, whereas (3) includes firms that were in overdue after buffer release conditional of not being in overdue before. *Prudential filter* is recorded at its amount in 2008q3 (just before the release) and expressed in percent of RWA. Capital adequacy ratio, share of NPL and bank total assets are taken from 2008q3. Overdue controls for specific firm $i$'s overdue in bank $j$. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We find that the prudential filter release increased loan loss provisioning. Model (1) in Table 4 shows the results for the sample of firms that were past due with loan repayment in 2009q3 for at last one day. For the same firm the coverage ratio increased by 8.4 p.p. more in banks that held a 1 p.p. higher capital buffer. Next, we use a more strict criteria in sample selection and include only firms that were more than 90 days overdue. This threshold is typically used to classify borrowers as non-performing, so banks provision extensively only after it is bridged. The results, presented in column (2), confirm our previous findings. One might be concerned that for the majority of firms included in models (1) and (2) the coverage ratio is constant because they were in default for a long time and had been provisioned accordingly. This might indeed be the case. The average number of days overdue among defaulted firms is above 500 days. To address this issue we estimate a model for firms that became past due after the prudential filter abdication. They are new defaulters that banks provisioned for the first time after capital release. The results are shown in column (3) in Table 4. We find a positive effect that is similar in magnitude to our previous result. We re-confirm that the buffer release increased loss absorption of banks as intended by the policymakers.

We now address some firm-bank specificities that could influence our finding of increased provisioning. The longer the time in default the higher should be the coverage ratio, all else being equal. Firms, however, do not start to delay with loan repayment to all banks at the same time. There might be difference in the coverage ratio for the same firms across multiple banks. To address this we add overdue-in-loan-repayment as a control variable. For models (1) and (2) it is irrelevant. The reason for this is that the difference in overdue of 10 or 50 days is negligible for firms that have already been in overdue for a long time. Once the number of days in overdue becomes high, banks estimate that it is unlikely that a loan will be repaid and they provision accordingly. For new defaulters in model (3), however, this variable is found to be relevant. A firm that started to delay loan repayment with bank $A$ 50 days before it started to delay loan repayment with bank $B$, is expected to have on average a 5 p.p. higher coverage ratio in bank $A$ as compared to bank $B$.

The second determinant of loan loss provisioning is collateral. Omission of collateral is to some degree controlled for with fixed effects. They capture the total firm's collateral. Banks, however, differ in strategy and ability to engage a firm's collateral. Unfortunately, we cannot control for the exact amount of collateral pledged by firm $i$ in bank $j$. These data are not available. We instead asses the direction of bias assuming the collateral does affect loan loss provisioning.

The bias depends on the correlation between provisioning, collateral and the prudential filter.

First, we establish that the prudential filter and collateral are positively correlated by excluding a negative one. Banks that held a higher filter also held lower collateral. We know that banks with a higher filter suffered smaller losses in the period 2009-2014.[20] Lower losses imply that those banks held more and better collateral. It is reasonable to assume that banks with a higher filter held more or better collateral. This implies the filter and collateral were positively correlated.

Next, we know that collateral and loan loss provisions are negatively correlated. This follows from basic accounting rules. Had loans been fully collateralized, there would be no need for provisions.

Finally, we determined that our omitted variable (collateral) is negatively correlated with the dependent variable (loan loss provisions) and positively correlated with our target variable (prudential filter). Therefore, if a prudential filter acts as a proxy for collateral, the coefficient will be downward biased. Our estimates of the effect of the capital buffer on provisioning represent a lower boundary on the coefficient estimate.

[20]The correlation between total bank losses in the period 2009-2014 expressed as a share of pre-crisis assets and the amount of prudential filter in 2008q3 (in % of RWA) is equal to -0.3.

# 5 Conclusion

This paper studies a unique experiment in the Slovenian banking system in 2007-2010. The experiment is called the prudential filter and it acted like a countercyclical capital buffer. In 2008q4, an exogenous shock caused the prudential filter abdication. It increased capital by 0.8% of risk-weighted assets. We estimate how this release of capital, akin to a countercyclical capital buffer, affected the banking system at the start of the financial crisis.

In 2006, Slovenian banks adopted IFRS. This led to a change in the way loan loss provisions and impairments were calculated. Fearing that the new method would decrease loan provisions, the Bank of Slovenia introduced a prudential filter. It was calculated as the difference between provisions and impairments calculated under the IFRS and the old Slovenian Reporting Standards rules. The prudential filter was used as a deduction from capital in the calculation of bank's capital adequacy ratio. The deduction item forced banks to hold more capital. The prudential filter was abdicated at the start of the financial crisis in Slovenia in 2008q4. Following its release the capital ratio of the banking system increased by 0.8 percentage point.

The prudential filter is similar in nature to a countercyclical buffer. It accumulated bank capital in times of excess credit growth and released it at the start of the crisis. Our study contributes to the literature on the countercyclical capital buffer by providing empirical results of a situation akin to a release of countercyclical capital buffer.

We investigate the effects of the release of the prudential filter on credit growth using loan-level data from the Slovenian credit register. We find that three quarters after the release, credit growth for the same firm, borrowing from at least two different banks, was on average 11 p.p. higher in a bank that had a 1 p.p. higher capital buffer. This result is robust to model specifications and the credit growth horizon. It suggests that the CCyB, which is designed to smooth credit growth, increased credit at the start of the crisis.

The second finding is that solid firms benefit most from the buffer release. This is important information for policymakers and banking regulators. It shows that by releasing the capital buffer, banks channel the new crediting capacity to healthy firms. They act countercyclical. This intensifies the positive effect of the buffer on the real economy.

Finally, banks use an additional loss-absorption-capacity that arises with a buffer release, to provision more for defaulted borrowers. This is a desired result since a delay in loan-loss recognition prolongs and intensifies the effect of a financial crisis.

Our investigation provides empirical support in favor of the effectiveness of capital based macroprudential instruments.

## References


David Aikman, Benjamin Nelson, and Misa Tanaka. Reputation, risk-taking, and macroprudential policy. *Journal of Banking & Finance*, 50:428–439, 2015.

Q. Farooq Akram. Macro effects of capital requirements and macroprudential policy. *Economic Modelling*, 42:77–93, 2014.

Bruce Arnold, Claudio Borio, Luci Ellis, and Fariborz Moshirian. Systemic risk, macroprudential policy frameworks, monitoring financial systems and the evolution of capital adequacy. *Journal of Banking & Finance*, 36(12):3125–3132, 2012.

Christoph Carl Basten and Catherine Koch. Higher bank capital requirements and mortgage pricing: evidence from the countercyclical capital buffer (CCB). Technical report, BIS Working Paper No 511, 2015.

BCBS. Basel III: A global regulatory framework for more resilient banks and banking systems. Technical report, Basel Committee on Banking Supervision, Basel, 2010.

BCBS. Frequently asked questions on the basel III countercyclical capital buffer. Technical report, Basel Committee on Banking Supervision, Basel, 2015.

Anne Beatty and Scott Liao. Do delays in expected loss recognition affect banks willingness to lend? *Journal of Accounting and Economics*, 52, 2011.

Marcus Behn, Rainer Haselmann, and Paul Wachtel. Procyclical capital regulation and ledning. *Journal of Finance*, 71:919–956, 2016.

Crisitina Biu, Harald Scheule, and Eliza Wu. The value of bank capital buffers in maintaining financial system resilience. *Journal of Financial Stability*, 33:23–40, 2017.

Emilia Bonaccorsi di Patti and Enrico Sette. Did the securitization makret freeze affect bank lending during the financial crisis? Evidence from a credit register. *Journal of Financial Intermediation*, 25:54–76, 2016.

Arjana Brezigar-Masten, Igor Masten, and Matjaž Volk. Discretionary credit rating and bank stability in a financial crisis. *Eastern European Economics*, 53(5):377–402, 2015.

Michał Brzoza-Brzezina, Marcin Kolasa, and Krzysztof Makarski. Macroprudential policy and imbalances in the euro area. *Journal of International Money and Finance*, 51:137–154, 2015.

Eugenio Cerutti, Stijn Claessens, and Luc Laeven. The use and effectiveness of macroprudential policies: new evidence. *Journal of Financial Stability*, 28:203–224, 2017.

Stijn Claessens. An overview of macroprudential policy tools. Technical report, IMF Working Paper, 14/214, 2014.

Gabriele Galati and Richhild Moessner. Macroprudential policy: a literature review. *Journal of Economic Surveys*, 27(5):846–878, 2013.

Hans Gersbach and Jean-Charles Rochet. Capital regulation and credit fluctuations. *Journal of Monetary Economics*, 2017.

Marco Gross, Christoffer Kok, and Dawid Żochowski. The impact of bank capital on economic activity-evidence from a mixed-cross-section gvar model. Technical report, ECB Working Paper Series 1888, 2016.

Timotej Homar and Sweder van Wijnbergen. On zombie banks and recessions after systemic banking crises. Technical report, CEPR Discussion Papers 10963, 2015.

Maria Iosifidi and Sotirios Kokas. Who lends to riskier and lower-profitability firms? evidence from the syndicated loan market. *Journal of Banking & Finance*, 61:S14–S21, 2015.

Gabriel Jiménez, Atif R Mian, José-Luis Peydró, and Jesús Saurina. Local versus aggregate lending channels: the effects of securitization on corporate credit supply in spain. Technical report, National Bureau of Economic Research, 2010.

Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesús Saurina. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *The American Economic Review*, 102(5):2301–2326, 2012.

Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesus Saurina Salas. Macroprudential policy, countercyclical bank capital buffers and credit supply: Evidence from the spanish dynamic provisioning experiments. *Journal of Political Economy*, 125:2126–2177, 2017.

Mahdi Ebrahimi Kahou and Alfred Lehar. Macroprudential policy: A review. *Journal of Financial Stability*, 29:92–105, 2017.

Asim Ijaz Khwaja and Atif Mian. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *The American Economic Review*, pages 1413–1442, 2008.

Joseph Noss and Priscilla Toffano. Estimating the impact of changes in aggregate bank capital requirements on lending and growth during an upswing. *Journal of Banking & Finance*, 62: 15–27, 2016.

Bank of Slovenia. Report of the BoS on the causes of the capital shortfalls of banks and the role of the Bank of Slovenia as the banking regulator in relation to the recovery of banks in 2013 and 2014. Technical report, 2015.

Official Gazette of the Republic of Slovenia. Regulation on the assesment of credit risk losses of banks and savings banks. Technical report, 2005, No. 67a.

Official Gazette of the Republic of Slovenia. Regulation on the assesment of credit risk losses of banks and savings banks. Technical report, 2005, No. 67b.

Official Gazette of the Republic of Slovenia. Regulation on the assesment of credit risk losses of banks and savings banks. Technical report, 2015, No. 50.

Joe Peek and Eric S. Rosengren. Unnatural selection: Perverse incentives and the misallocation of credit in japan. *The American Economic Review*, 95(4):1144–1166, 2005.

Margarita Rubio and José A Carrasco-Gallego. The new financial regulation in basel III and monetary policy: A macroprudential approach. *Journal of Financial Stability*, 26:294–305, 2016.

William J Tayler and Roy Zilberman. Macroprudential regulation, credit spreads and the role of monetary policy. *Journal of Financial Stability*, 26:144–158, 2016.