Empirical Evidence on the Effectiveness of Capital Buffer Release*

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With the new regulatory framework, known as Basel III, policymakers introduced a countercyclical capital buffer. Due to its recent introduction, empirical research on its effects is limited. We analyze a unique policy experiment to evaluate the effects of buffer release. In 2006, the Slovenian central bank introduced a temporary deduction item in the capital calculation, creating an average capital buffer of 0.8 percent 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 behavior. After its release, firms borrowing from banks holding 1 pp higher capital buffer received 11 pp more in credit. Also, we find the impact was greater for healthy firms, and it increased loan loss provisioning for firms in default.

JEL Codes: G01, G21, G28.

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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 buildup of system-wide risk, banks are required to build a capital buffer (of up to 2.5 percent of risk-weighted assets) in the form of Common Equity Tier 1 capital. It is to be released in downturns to avoid regulatory capital requirements reducing credit growth, which could undermine the performance of the real economy and result in additional credit losses (Basel Committee on Banking Supervision 2015).

With the outbreak of COVID-19, banks supervised by the European Central Bank (ECB) were allowed to operate below the level of Pillar 2 Guidance (P2G) capital and capital conservation buffer (CCB) requirements.[2] These measures were further enhanced by the relaxation of the CCyB by national macroprudential authorities.[3] Such unprecedented relaxation of capital requirements intends to support lending and aims to mitigate second-round effects of the lockdown measures via the banking sector.

Unfortunately, these measures are recent and there is little evidence of their effectiveness. In the EU, CCyB was introduced in 2016 and COVID-19 marks its first release. Our paper provides empirical evidence on the effectiveness of capital buffer release following adverse economic conditions. We study a unique policy experiment that mirrors the workings of a capital buffer release at the start of the 2008 financial crisis in the Slovenian banking system. We study its impact on bank lending and loss-absorption capacity. Our findings

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

[2] https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200312~43351ac3ac.en.html.

[3] Until July 2020, 13 EU countries at least partial released the CCyB and only 5 countries preserved a positive buffer (for more information see https://www.esrb.europa.eu/national_policy/ccb/html/index.en.html).

are favorable and support the actions undertaken by the policymakers and supervisors in response to the COVID-19 outbreak.

Current empirical research on CCyB relies on models that proxy the effects of CCyB by using changes in capital ratios.[4] This approach could be flawed. First, capital ratios are slow to adjust. CCyB release is sudden and generates a discontinuous shift in capital ratios. Second, changes in capital ratios are endogenous. They are subject to banks' own decisions. Endogenous capital changes may have a different effect on credit supply compared with an exogenous CCyB release. In contrast, we employ a policy experiment where the release of a capital buffer is exogenous concerning the Slovenian banking system.

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 fewer 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 the prudential filter. Due to it, banks held additional capital from 2006:Q1 to 2008:Q3. In response to the financial crisis, it was abdicated. It amounted to 0.8 percent of a system's risk-weighted assets (RWA) and acted like a countercyclical buffer. Banks accumulated capital in good times only to use it as a buffer for losses in bad times.

To investigate the effects of capital buffer release in distressed economies, we consider the Slovenian banking system. It was one of the most severely affected banking systems in Europe in the global financial crisis. By 2013 its share of non-performing loans (NPL) reached 25 percent for the corporate sector. According to Hartmann, Huang, and Schoenmaker (2018), this places it third according to recapitalization costs among European countries, making it suitable as a case study of buffer release in a distressed European banking system.

[4]Akram (2014) uses a vector error-correction model and Gross, Kok, and Żochowski (2016) a global vector autoregressive model. 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.

Our identification strategy follows Khwaja and Mian (2008). We estimate the difference in a 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.

We found evidence that a higher capital buffer caused higher loan growth after the release. In our benchmark model, for the same firm borrowing from at least two different banks, credit growth was 5–11 percentage points (pp) higher in a bank with a 1 pp higher capital buffer before its release.[5] In addition, the probability of loan increase for a firm was 5.8 pp higher with a bank with 1 pp 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 pp more in banks with a 1 pp higher buffer, for firms that defaulted at the time of buffer release. We find strong evidence for stabilizing effects of capital buffers. Several robustness tests confirm the validity of our results.

Our findings complement theoretical and simulation-based models that argue in favor of capital buffers. Borsuk, Budnik, and Volk (2020) explore the role of capital buffers in containing the reduction of lending to the real economy during the COVID-19 crisis. Their analysis employs a large semi-structural model that connects banks and macroeconomy. They find that capital buffers lead to higher lending, with positive effects on gross domestic product (GDP) and lower credit losses. Aikman, Nelson, and Tanaka (2015) use a three-period model and Rubio and Carrasco-Gallego (2016) a dynamic stochastic general equilibrium (DSGE) model in which CCyB reduces excess credit buildup. Brzoza-Brzezina, Kolasa, and Makarski (2015) employ a DSGE model to show that CCyB mitigates credit

[5]Related literature investigates how lending is affected by capital increases (as opposed to its releases). An overview of empirical literature can be found in Dagher et al. (2016). In Dagher et al. (2016), a 1 pp higher capital decreases lending from 0.15 pp to 8 pp, depending on the model and horizon considered (see Tables 4A and 4B).

imbalances in the buildup phase; however, loan-to-value (LTV) restriction is shown to be more effective in this respect. We show that 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 is provided by Biu, Scheule, and Su (2017), who apply simulation techniques to show that a higher capital buffer reduces system-wide losses and therefore increases 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 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 we 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. In our experiment, the release is caused by a crisis that 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 carry implications for policymakers and supervisors. We show that capital release increases bank lending in a crisis period. Further, we found that the increased lending was largely directed towards less risky firms, those without delays in loan repayments. This is helpful because it intensifies the positive effect of a capital buffer release on the real economy. An additional favorable effect is faster recognition of losses by banks. As shown by Beatty and Liao (2011) and van Wijnbergen and Homar (2014), fast recognition of losses 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 by more.

The paper is structured as follows. In the next section, we introduce the prudential filter and macroeconomic environment in Slovenia for the period in which 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 into the functioning of the prudential filter. The prudential filter was introduced at the beginning of 2006 and released at the end of 2008 when the crisis hit. We first discuss the macroeconomic and banking environment in Slovenia in the period 2007–10 and then the prudential filter.

2.1 Macroeconomic and Banking Environment

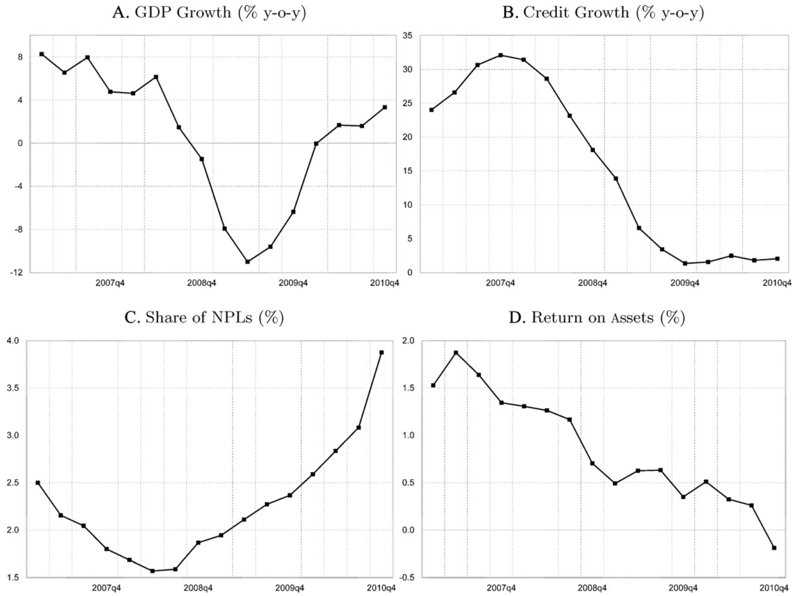
The period surrounding the buffer release is characterized by a transition from a period of high economic and credit growth to a deep recession. After a period of high growth, GDP turned negative in 2008:Q4 (see Figure 1).[6] At the time, the central bank of Slovenia released the prudential filter. In 2009 GDP contracted further, followed by a mild recovery in 2010. The recession severely affected the banking sector. Credit growth declined to 0 percent in 2009. A freeze of the European interbank market, which 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.[7] Concurrently, bank profit declined. In 2010 it turned negative and Slovenian banks started recording losses. Between 2009–14 these losses amounted to 10 percent of total pre-crisis assets.

The Bank of Slovenia decided to release the prudential filter in 2008:Q4. 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. An estimation methodology that does not control for a fall in loan demand will lead to

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

[7]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 in Slovenia in 2007–10



Source: Bank of Slovenia, own calculations.

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 capital requirements, acting as CCyB. These requirements were released in 2008:Q4. This section describes the nature and regulatory aspects of the prudential filter.

In 2002 the European Parliament and Council adopted the 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

Table 1. Provision and Impairment Rates Valid in the 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 be 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 Gazette of the Republic of Slovenia (2005a, Article 22). Definitions of asset classes can be found in the same document, under Article 11.

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.

A bank loan carries a risk that a borrower may not repay it. To account for such losses, banks apply impairments which are the difference between the carrying amount of the loan and the recoverable amount.[8] They are conventionally expressed in percentages of the carrying amount of the loan. A bank records the impaired value of the loan on the assets side of its balance sheet. 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 bank's capital. The bottom line is that the higher/lower the impairments, the more/less capital a bank needs to hold to be compliant with 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

[8]This definition is derived from the official definition published in the Official Gazette of the Republic of Slovenia (2015).

loan was downgraded to a higher risk bucket, the bank had to apply a higher provision rate, irrespective of materialization of losses.

In 2006, Slovenian banks traversed to IFRS. Under the IFRS, provision and impairment rates were no longer set by the Bank of Slovenia. They were set by the banks using a 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 materialized losses. In contrast, under the historical approach, the loan loss provisions are recorded regardless of actual losses.

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

To mitigate the reduction in bank capital, the Bank of Slovenia amended the rules on credit risk calculation[9] and the regulation on bank capital calculation.[10] The amendments stated that, for regulatory purposes, the banks were required to introduce a (own funds) deduction item.[11] 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 because for these loans a bank thoroughly assesses the expected cash flow and provisions accordingly.

Since prudential filter was deducted from Tier 1 capital, it forced banks to hold higher capital from 2006:Q1 to 2008:Q3. This

[9]See Official Gazette of the Republic of Slovenia (2005a).
[10]See Official Gazette of the Republic of Slovenia (2005b).
[11]Own funds is a broader definition of capital that also includes Tier I capital and secondary capital.

approximated the effect of a countercyclical buffer buildup if it existed at the time.

Our identification strategy relies on the filter release being caused exogenously by the financial crisis. To this purpose, the results include a placebo test. In addition, here we argue that the filter release remained uncertain until the start of the financial crisis in Slovenia.

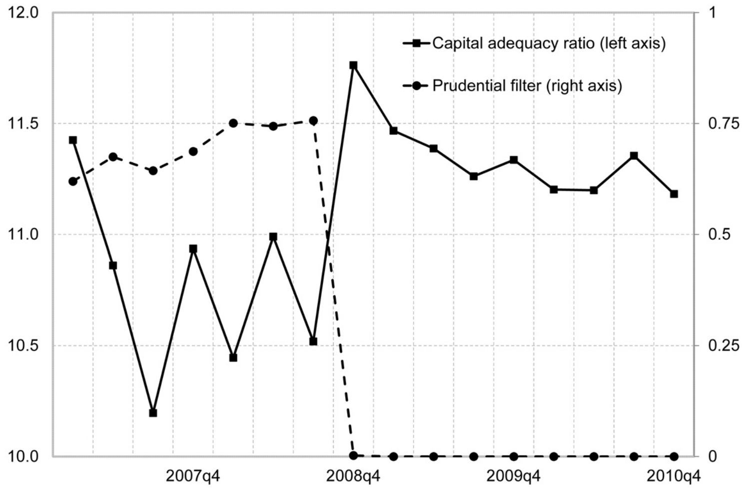
The special report of the Bank of Slovenia for the National Assembly on the causes of the capital shortfalls of banks[12] describes that "banks and auditors moved to have it ([prudential filter]) revoked several times" (Bank of Slovenia 2015). They were rebuffed until December 2007. Even then, the Bank of Slovenia deferred abdication "until a slowdown in the excessive lending activity of the banks [October 2008]" (Bank of Slovenia 2015). Uncertainty regarding its release is further supported by national newspaper articles. They report on the dissatisfaction of commercial banks with the deferment of the prudential filter abdication. In October 2008, a leading national newspaper reported that "at the beginning of the year [2008] the central bank governor . . . opposed abdication of the filter because of excess credit activity in the previous year (author's translation, Zimic 2008)." This points toward a substantial degree of uncertainty regarding the timing of the filter's abdication before its actual release in response to the financial crisis.

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 abdicated the prudential filter in 2008:Q4, at the first signs of the 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 point. Sudden increases in bank capitalization implied that banks could use excess capital for either lending or absorption of credit losses, which is analogous to a countercyclical capital buffer release.

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 percent of RWA before the release and zero afterwards.

[12]In English, p. 41, section Introduction of an own funds deduction item.

Figure 2. Weighted Mean of Capital Adequacy Ratio and Prudential Filter in Percent of RWA, 2007–10



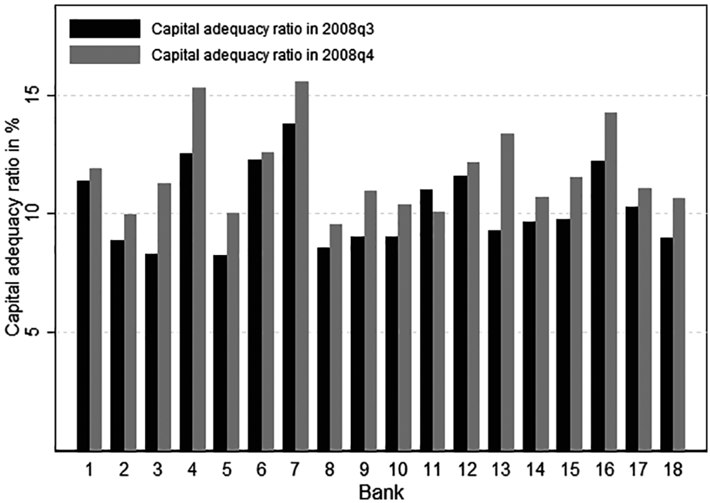
Source: Bank of Slovenia, own calculations.

The capital adequacy ratio (solid line in Figure 2) displays a mirrored picture. It increased almost one-to-one when the prudential filter was released. The prudential filter increased capital requirements during an expansionary period and alleviated them in the time of the financial crisis.

Figure 3 shows the capital adequacy ratio (CAR[13]) by banks before and after the release. The prudential filter caused an increase 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 2008:Q3 and 2008:Q4, say recapitalization or realization of losses. This explains a decrease in the CAR for the one bank, which could not arise due to the prudential filter release. The prudential filter can only increase the capital available to a bank.

[13]Throughout this paper the acronym CAR stands for capital adequacy ratio and is not to be confused with cumulative abnormal returns.

Figure 3. Capital Adequacy Ratio Before the Release (2008:Q3) and After It (2008:Q4), Across Banks

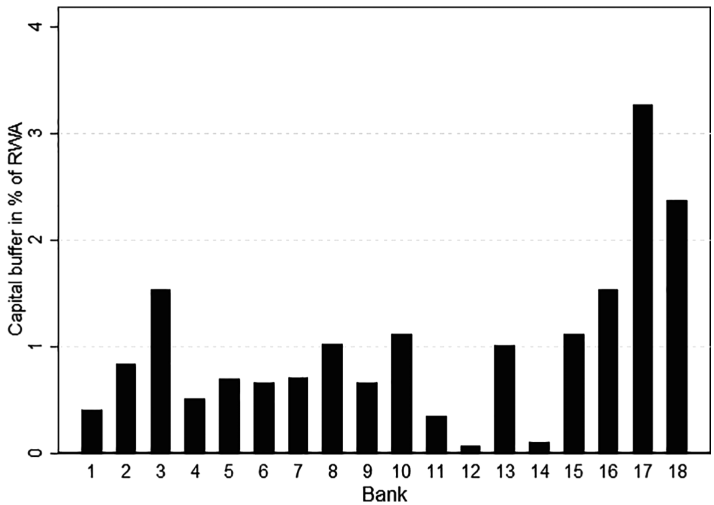


Source: Bank of Slovenia, own calculations.

Figure 4 shows the size of the prudential filter in terms of RWA before its release in 2008:Q3. We tested if banks that were required to hold a higher prudential filter lent and provisioned by more at the beginning of the crisis. Our identification strategy (described in Section 3.1) relies on firms taking loans with multiple banks subject to varied prudential filter requirements. Loan-level data coupled with between-bank prudential filter variability enabled us to estimate the effect of a 1 pp increase in the capital buffer on bank lending while controlling for loan demand. Eight banks held prudential filters above 1 percent and eight in the range of 0.3–1 percent of RWA. Two banks held prudential filters close to 0 percent. With release prudential filter translated into an increase in capital adequacy by the same amount.

There is a conceptual difference between the prudential filter and the CCyB. Under the CCyB the rate of additional capital is the same for all banks (up to 2.5 percent of RWA). On the other hand, the prudential filter was bank specific. It ranged from close to 0 percent of RWA to more than 3 percent. The fact that the prudential filter varied facilitates our analysis. Its variability across banks enabled

Figure 4. Prudential Filter in 2008:Q3 in Percent of RWA, Across Banks



Source: Bank of Slovenia, own calculations.

us to estimate the average effect of a 1 pp increase in the capital buffer. Note also that the CCyB is applied by increasing the minimum capital requirement, whereas the prudential filter decreased the accounting value of capital that entered the calculation of capital adequacy ratio. Regardless, in practice, they both increase the capital available to banks at the time of its 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

We identified the effects of buffer release in a loan-level model. Its key advantage is that it controls for loan demand and thereby yields unbiased and consistent estimates of coefficients. The methodology used in this section was put forward by Khwaja and Mian (2008). It was further adopted by Jiménez et al. (2010, 2017), Behn, Haselmann, and Wachtel (2016), Bonaccorsi di Patti and Sette (2016), and others.

Khwaja and Mian (2008) use a clever estimation technique that allows one to control for loan demand. Suppose that we have N borrowers with at least two banking relations in a given period:

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

where y_{ij} stands for borrower i's loan growth ($i = 1 \ldots N$) in bank j ($j = 1 \ldots M$) in the period surrounding the buffer release (see Section 3.2). X_{ij} represents a $K \times 1$ vector of policy and control variables. D_i is a dummy variable that takes the value of 1 for individual i and 0 elsewhere. It absorbs firm-specific (unobservable) loan demand and other firm-specific characteristics. It enables us to estimate the effect of policy variable X_{ij} on loan growth y_{ij}, while controlling for unobservable firm-specific characteristics.

In our case, we estimate the effect of prudential filter release on a bank's loan supply and loan loss provisioning. In the first case the dependent variable is loan growth, and in the second it is the change in coverage ratio realized by bank j to firm i. Two key factors defining 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.

3.2 Data

We used data from the credit register of the Bank of Slovenia. It contains multiple observations per individual borrower for each period. Having multiple observations per borrower allowed us to control for individual-specific fixed effects. Loans were obtained from the population of 18 banks. On the level of a borrower these are only available for firms. Households loans are reported cumulatively across risk buckets and cannot be used in a loan-level model. By considering only corporate loans, we still considered nearly all loans to the private non-financial sector. Loans to households represented only 23 percent of all credit to the private non-financial sector in 2008.[14]

The first important step in data preparation was to select an appropriate period to be used for calculating loan growth. Our baseline period is credit growth between one quarter before the prudential filter release (2008:Q3) and three quarters after the release (2009:Q3). One could argue that the chosen period is subjective. Therefore, we also estimated the model on horizons from one to four quarters after the release and report on those results.

For identification purposes, we restricted our sample to firms indebted to at least two banks. After imposing this restriction we were left with 7,882 firms. They account for 22.3 percent 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 accounts for 84.2 percent of loans. Thus the data are representative and cover a large share of the total amount of lending tofirms. Next, for estimating the effect of buffer release on lending, we restricted our sample to performing firms alone. We excluded 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. This increase in the loan amount is caused by accounting regulation and could be spuriously correlated with our regressors. Lastly, to eliminate outliers, we excluded firms of the 1st and 100th percentile of the distribution of our dependent variables.

In estimating the effect on loan loss provisioning, we focused on firms that are either in default or have difficulties in repaying the loan. Only these need to be provisioned extensively and account for the bulk of loan loss reserves. If we included the performing firms, we would find a much smaller or even insignificant effect on provisions. The reason is that there is no need to increase provisions for

[14]We also performed an aggregate analysis with loans to households included. We estimated a bank-level dynamic panel-data model with loan growth to firms and households as the dependent variable. 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.

Table 2. Summary Statistics

Variable	Unit	Mean	Std. Dev.	Min.	Max.	Obs.
Loan Growth	%	14.79	105.36	–90.47	1,166.67	11,984
Loan Increase	0/1	0.34	0.47	0	1	11,984
Change in Coverage Ratio	pp	11.30	28.46	–81.70	92.86	1,429
Prudential Filter	%	0.72	0.36	0.07	1.53	11,043
Total Assets	EUR bln.	5.16	5.33	0.02	15.10	11,984
Capital Adequacy Ratio	%	10.07	1.60	8.22	15.23	11,984
Share of NPLs	%	2.66	1.20	0.05	4.77	11,984
Bank Credit Growth	% y-o-y	25.72	13.73	9.80	54.08	11,984

Source: Bank of Slovenia, own calculations.
Note: Loan growth is calculated for the period 2008:Q3–2009:Q3. Credit increase is a dummy variable equal to 1 if firm i loan amount increased in bank j in period 2008:Q3–2009:Q3. Prudential filter, total assets, capital adequacy ratio, share of NPLs, and bank credit growth are reported at their values from 2008:Q3, 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.

firms that repay loans regularly. This follows from the IFRS-incurred loss provisioning model. Similarly, as in the case of the loan growth analysis, we eliminated outliers.

Table 2 shows summary statistics for the variables included in the model. Credit growth is calculated as percentage growth in credit between one quarter before and the third quarter after its release (2008:Q3 to 2009:Q3). Mean credit growth is 15 percent. Loan increase is a dummy variable equal to 1 if firm i's loan amount increased in bank j in the period 2008:Q3–2009:Q3. Thirty-four percent of the firms increased their indebtedness after the release. The second variable of interest is the change in coverage ratio. It has a mean equal to 11.3 pp.[15] It is calculated only for the non-performing firms. All policy and control variables are included in the model at their values in 2008:Q3, i.e., just before the release. The average value of our main policy variable, the prudential filter, was

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

0.72 percent in 2008:Q3.[16] Bank size is measured with total assets. Its average value in 2008:Q3 was about EUR 5 billion. Average capital adequacy ratio, the share of non-performing loans, and year-over-year (y-o-y) bank credit growth before the filter release were 10.1 percent, 2.7 percent, and 25.7 percent, respectively.

4. Results

We now discuss the results. We investigated if banks with a higher amount of capital buffer lent more at the beginning of the crisis in 2009. Next, we explored the characteristics of firms that benefited from additional lending. Lastly, we verified if banks used extra loss-absorption capacity to increase provisioning for bad loans. By answering these questions, we evaluate the effectiveness of the capital buffer release policy.

Table 3 shows the effect of the buffer release on bank lending. The dependent variable is firm i credit growth for a loan taken with bank j in the period 2008:Q3–2009:Q3. We control for firm-specific demand with firm-fixed effects and include several controls for bank-level factors. 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 the prudential filter, credit growth was 11.1 pp higher if the bank had a 1 pp higher capital buffer.[17] By using standard errors clustered at the bank level, this coefficient is statistically significant at conventional levels.[18] This implies that capital buffer release indeed increases bank lending.

We now extend our baseline model by adding the credit growth in the year before the 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 filter. It might reflect higher credit growth of banks that incidentally also held higher prudential filters.

[16] This is a non-weighted average expressed from the restricted sample. Its maximum value is 1.53 percent, whereas this same value is more than 3 percent when expressed from the unrestricted sample. Figure 4 plots the unrestricted sample.

[17] Compared with the standard deviation of capital adequacy ratio, which is 0.36 pp, an average increase of 0.8 pp is considered substantial. If buffer instead increased by 0.36 pp, the loan growth would increase by 4 pp.

[18] Standard errors and p-values are corrected for small bank-level cluster size.

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

	(1)	(2)	(3)	(4)	(5)
Prudential Filter	0.111**	0.118**	0.118**	0.124**	0.130**
	(0.049)	(0.051)	(0.044)	(0.048)	(0.057)
Capital Adequacy Ratio	0.016	0.020*	0.014	0.017	0.018
	(0.011)	(0.010)	(0.010)	(0.011)	(0.124)
Share of NPL	0.024*	0.032*	0.018	0.024	0.024
	(0.013)	(0.016)	(0.011)	(0.014)	(0.014)
Total Assets	–0.000*	–0.000	–0.000*	–0.000*	–0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit Growth		0.131			
		(0.167)			
Share of Interbank Funding			–0.122		
			(0.157)		
Prudential Filter*$I(Overdue > 0)$				–0.212**	
				(0.075)	
Prudential Filter*Rating					–0.048
					(0.032)
Constant	–0.124	0.231	–0.048	–0.134	–0.145
	(0.146)	(0.177)	(0.154)	(0.142)	(0.164)
Firm FE	Yes	Yes	Yes	Yes	Yes
No. of Observations	11,043	11,043	11,043	11,043	11,043

Source: Bank of Slovenia, own calculations.
Note: The table reports the estimation results for the loan-level differences-in-differences model. The dependent variable in all the equations is firm i loan growth in bank j in period 2008:Q3–2009:Q3 (10 percent is expressed as 0.1). Prudential filter is its amount in 2008:Q3 (just before the release), expressed in percent of RWA. Capital adequacy ratio, share of NPL, bank total assets, and share of interbank funding are taken from 2008:Q3. Credit growth is bank-specific credit growth in the year before the prudential filter release. $I(Overdue > 0)$ is an indicator equal to 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). Standard errors (in parentheses) are clustered at the bank level. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

As shown with model 2 in Table 3, the results are robust. Even when controlling for a bank's past 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 to be insignificant.

Next specification controls for the simultaneity of interbank credit market freeze and the buffer release. Before its release, the

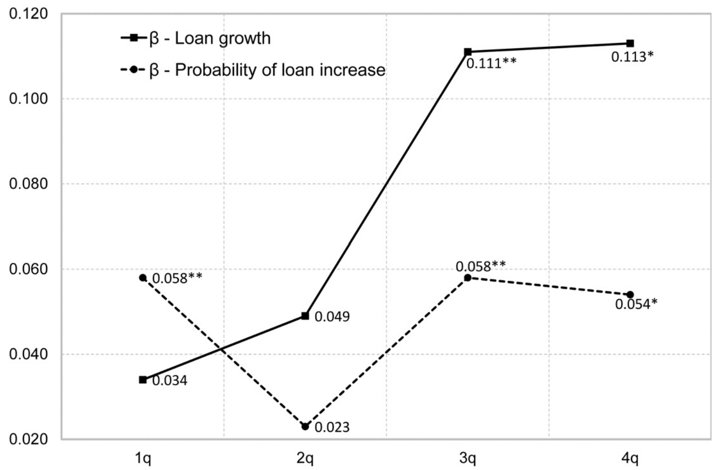
Slovenian banking system relied on interbank funding. Interbank funding increased from 10 percent in 2002 to approximately 40 percent of total funding in 2008:Q3. This share increased to 55 percent for foreign-owned banks. With the Lehman Brothers bankruptcy, the interbank market froze. This exogenous supply shock coincides with the timing of the buffer release. Failing to control for it could induce a bias in our estimates. Hence, specification 3 controls for the share of interbank financing. Despite controlling for it, the coefficient on the prudential filter remains the same in magnitude and statistical significance.

Our next set of results investigates which firms benefited from the positive effect of the filter release. Note that this was a period when the crisis began and non-performing loans started to accumulate. In response to it, banks could engage in evergreening of riskier loans. This practice reduces the pressure of loan loss provisions on bank capital and is documented in Peek and Rosengren (2005). It would be undesirable for the capital buffer release to amplify this effect.

We verified this by interacting prudential filter with two variables that measure firm riskiness. First, we used the number of days overdue in loan repayment by firm i to bank j. Model 4 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. Second, we used the credit rating assigned by bank j to firm i. It takes a value from 0 (rating A) to 4 (rating E). The coefficient on the interaction term in specification 5 is negative, although 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 an outcome desired by the policymakers.

We have shown that the capital buffer release increased loan growth in a specific time horizon, 2008:Q3–2009:Q3. We now verify the robustness of the results to the chosen time horizon. 2008:Q3 was used as a cut-off date before the prudential filter release. We kept this date fixed to stay as close as possible to the time of the buffer release. We did not wish to contaminate the dependent variable with other effects that transpired. For the same reason, we did not consider periods beyond one year after its release.

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.
Note: Significance: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Figure 5 presents the results for horizons that span from one to four 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 the third and fourth quarter after the release.[19] This is to some extent expected since banks typically need time to reallocate spare capital.

We also estimated the probability of a loan increase following the release of the prudential filter. The dependent variable is equal to 1 if firm i's amount of loan borrowed from bank j has increased in the examined period. We used 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 might be, despite certain exclusions, still present. The results are presented in Figure 5. Comparable to credit growth, the release of the capital buffer increases the probability of loan growth. We find that a firm

[19]Beyond the fourth quarter, the effects of buffer release is diminishing.

Table 4. The Effect of Capital Buffer Release on Bank Loan Loss Provisioning

	(1)	(2)	(3)
	Overdue$_{2009q3}$ > 0	**Overdue$_{2009q3}$ > 90**	**Overdue$_{2008q3}$ = 0, Overdue$_{2009q3}$ > 0**
Prudential Filter	0.084**	0.077**	0.086*
	(0.031)	(0.029)	(0.047)
Capital Adequacy Ratio	0.001	0.012	0.021
	(0.010)	(0.008)	(0.021)
Share of NPL	–0.014	–0.007	–0.014
	(0.016)	(0.009)	(0.022)
Total Assets	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Overdue	0.000	0.000	0.001***
	(0.000)	(0.000)	(0.000)
Constant	–0.026	0.006	–0.235
	(0.098)	(0.092)	(0.233)
Firm FE	Yes	Yes	Yes
No. of Observations	2,032	1,337	856

Source: Bank of Slovenia, own calculations.
Note: The table reports the estimates for the loan-level differences-in-differences model. The dependent variable in all the equations is the change in loan loss provisioning ratio between 2008:Q3 and 2009:Q3. The model is estimated for three subsamples: (1) and (2) include firms that had an overdue higher than 0 or 90 days, respectively, whereas (3) includes firms that were in overdue for the first time after the buffer's release. Prudential filter is recorded at its amount in 2008:Q3 (just before the release) and expressed in percent of RWA. Capital adequacy ratio, share of NPL, and bank total assets are taken from 2008:Q3. Overdue controls for firm i's overdue in bank j. Standard errors (in parentheses) are clustered at the bank level. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

had a 5.8 pp higher probability of a loan increase with a bank that held a 1 pp higher capital buffer.

We next explored the effect of capital release on bank loan loss provisioning. Due to a filter release, banks obtained spare capital. Spare capital increased their loss absorption capacity. However, a study by Brezigar-Masten, Masten, and Volk (2015) showed that banks intentionally underestimated the loan loss provisions when the non-performing loans started piling up in their balance sheets. We tested if banks with higher capital buffers provisioned more, thereby decreasing the underestimation of credit risk.

Results are presented in Table 4. The dependent variable is the change in the coverage ratio for each observation between 2008:Q3 and 2009:Q3. We controlled for firm fixed effects and focused on firms that were either in default or overdue. We present three different sets of results that depend on the firm's overdue.

We found 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 2009:Q3 for at least one day. For the same firm, the coverage ratio increased by 8.4 pp more with banks that held a 1 pp higher capital buffer. Next, we used stricter criteria in sample selection. We included 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. This could be because these firms were in default for a period that was long enough to be fully provisioned for. The average number of days overdue among defaulted firms is above 500 days. To address this issue, we estimated a model for firms that became past due after the prudential filter abdication. These were new defaulters that banks provisioned for the first time after capital release. The results are in column 3 of Table 4. As before, we find a stable and positive effect similar in magnitude to our previous results. We reconfirm that the buffer release increased the loss absorption of banks, as intended by the policymakers.

We now address some firm-bank characteristics that could influence our finding of increased provisioning following a buffer release. The longer the time in default, the higher should be the coverage ratio of a loan. Firms, however, do not start to delay loan repayment to all banks at the same time. There might be a difference in the coverage ratio for the same firm across multiple banks. To address this we add overdue-in-loan-repayment as a control variable. For models 1 and 2 this control is irrelevant. The difference in overdue of 10 or 50 days is negligible for firms that have been 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, as in model 3, 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 pp higher coverage ratio in bank A as compared with bank B.

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

The direction of (potential) bias, due to omission of collateral, will depend on the correlations between provisioning, collateral, and the prudential filter. First, we establish that the prudential filter and collateral are positively correlated. Banks that held higher filters incurred lower losses in 2009–14.[20] Next, we know that collateral and loan loss provisions are also negatively correlated. This follows basic accounting rules. Had loans been fully collateralized, there would be no need for provisions. Finally, if prudential filter acts as a proxy for collateral, the coefficient is expected to be downward biased. Our estimates of the effect of the capital buffer on provisioning represent a lower boundary on the coefficient estimate.

4.1 Robustness Checks

This section presents four sets of robustness checks.[21] First, we expand the sample by adding single-bank relation firms to (potentially) increase the external validity of our results. Second, we conduct a placebo test. It rules out that our results are driven by a particular set of confounding factors. Third, we evaluate the robustness of our results to unobserved confounders by using the bias adjustment approach of Oster (2019). And fourth, we apply a matching estimator to control for potential data imbalance and to control for variables that were omitted from the response regression (loan growth) but affect treatment assignment (buffer size). Robustness checks are applied to our benchmark model 1 in Table 3.

[20]The correlation between bank losses in 2009–14, expressed in terms of precrisis assets, and prudential filter in 2008:Q3 (in percent of RWA) is equal to –0.3.

[21]We thank the anonymous referees for their suggestions.

4.1.1 Sample Expansion

Khwaja and Mian (2008) control for firm-specific loan demand by relying on firms that borrow from multiple banks.[22] Single-bank firms are omitted.[23] Degryse et al. (2019) introduce an approach that does not rely on the presence of multiple banking relations. They replace the firm-specific dummy with a set of location-industry-size dummies.[24] Their model is identified if there are at least two firms in each location-industry-size bucket, regardless of the number of banking relations per firm.

The model of Degryse et al. (2019) requires stronger assumptions on firm-specific loan demand. Khwaja and Mian (2008) require loan demand of a single firm to be constant across banks, whereas Degryse et al. (2019) require it to be constant across all firms in the same location-industry-size bucket and the banks that they borrow from. Which method delivers externally valid estimates depends on the trade-off between the importance of the inclusion of single-bank firms versus the plausibility of the constancy of firm loan demand within location-industry-size buckets.

Table 5 presents the results. Following Degryse et al. (2019) we use two-digit NACE codes to form industry clusters (83), municipalities to form location clusters (213), and the number of persons employed to form size clusters (16).[25] This produces a total of 13.108 clusters which are granular enough to capture firm-specific loan demand.[26] We find that a 1 pp higher capital buffer increases loan growth by 9 pp. This is consistent with, but smaller than, our benchmark estimate (11.1 pp). We cannot say for certain if the marginally smaller estimate is the result of sample expansion or due to a less precise control for loan demand. However, both estimates of credit growth are substantial in economic terms.

[22]See section on identification strategy.

[23]These firms account for 79 percent of all non-financial corporations in our sample.

[24]In a dynamic setting their dummy variable is also time specific.

[25]These are internal Bank of Slovenia size clusters which are based on the Eurostat size clusters but are more detailed.

[26]We also estimated models with location clusters defined by regions (13), less granular size clusters (4), and industry clusters defined by one-digit NACE codes (20). The estimate of the coefficient on capital buffer ranged between 0.075 and 0.090 and always remained significant.

Table 5. The Effect of Capital Buffer Release on Bank Lending with Sample Expansion

	(1)
Prudential Filter	0.090**
	(0.039)
Capital Adequacy Ratio	–0.011
	(0.010)
Share of NPL	0.025
	(0.015)
Total Assets	–0.000
	(0.000)
Constant	0.126
	(0.119)
ILS FE	Yes
No. of Observations	36,708

Source: Bank of Slovenia, own calculations.
Note: The table reports the estimation results for the loan-level model of Degryse et al. (2019). Dependent variable is firm i loan growth in bank j in period 2008:Q3–2009:Q3 (10 percent is expressed as 0.1). Prudential filter is its amount in 2008:Q3 (just before the release), expressed in percent of RWA. Capital adequacy ratio, share of NPL, bank total assets, and share of interbank funding are taken from 2008:Q3. Credit growth is bank-specific credit growth in the year before prudential filter release. ILS FE stands for industry-location-size fixed effects. Standard errors (in parentheses) are clustered at the bank level. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.1.2 Placebo Test

In a placebo test we falsely assume that the buffer was released a year before its actual release, in 2007:Q4. In that period Slovenian economy recorded record GDP growth and was not affected by the crisis. This test verifies if the treatment effects (buffer release) were present before the policy change took place. Should the effects be present before the policy change took effect, it would indicate that our results are driven by confounding factors correlated with subsequent capital buffer release. It could also signal that buffer release was anticipated in advance.

Due to data limitations, we depart from the benchmark model (see specification 1 in Table 3). Capital adequacy is only available

Table 6. Placebo Test—Hypothetical Buffer Release in 2007:Q4

	Actual Release in 2008:Q4	Hypothetical Release in 2007:Q4
Prudential Filter	0.093*	0.007
	(0.052)	(0.095)
Leverage Ratio	0.882	0.358
	(0.626)	(1.268)
Share of NPL	0.025	–0.000
	(0.145)	(0.025)
Total Assets	–0.000	–0.000
	(0.000)	(0.000)
Constant	–0.041	0.432***
	(0.124)	(0.126)
Firm FE	Yes	Yes
No. of Observations	11,043	10,141

Source: Bank of Slovenia, own calculations.
Note: The table compares the estimation results of the actual and the placebo experiment. The dependent variable is loan growth in the one-year window around the treatment date (2008:Q3–2009:Q3 for real experiment and 2007:Q3–2008:Q3 for placebo test). All the control variables are dated one quarter before the treatment date. Standard errors (in parentheses) are clustered at the bank level. Significance: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

from 2008 onward, hence we replace it with leverage ratio expressed as the book value of capital to total assets.

Table 6 displays the results. To ensure that variable substitution does not affect the test, we first replicate our benchmark regression with the capital adequacy ratio replaced by the leverage ratio and keep the buffer release in 2008:Q4. The coefficient on the prudential filter remained of similar magnitude and statistical significance.

We then assumed a counterfactual buffer release in 2007:Q4. The second column displays the results. The coefficient on the prudential buffer is close to zero and statistically insignificant (the exact p-value is 0.945). We conclude that it is unlikely that a correlated (omitted) confounder or the anticipation of buffer release drives our results.

Table 7. Robustness to Omitted-Variable Bias

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline Model $\widetilde{\beta}$	**Zero Model $\mathring{\beta}$**	**β* with $\delta = -1$**	**β* with $\delta = 1$**	**Within Conf. Interval?**	**δ for $\beta^* = 0$**
β	0.111	0.061	0.075	0.146	Yes	–3.158
R^2	0.592	0.000				

Source: Bank of Slovenia, own calculations.
Note: The table shows the bounds of the estimated effect of the prudential filter on lending using Oster (2019) methodology. The restricted model includes the same set of controls as specification (1) in Table 3. Zero model includes only prudential filter and intercept. The bounds are calculated assuming $R_{\max} = 1$.

4.1.3 Bias Adjustment for Selection on Unobservables

Based on Altonji, Elder, and Taber (2005), Oster (2019) developed a test for assessing bias from unobservable factors. The idea is to compare the coefficient on prudential filter from a regression with the full set of controls ($\widetilde{\beta}$) with the coefficient from a regression with intercept only ($\mathring{\beta}$). This delivers a *bounded estimator* ($\beta^\star$) defined as follows:

$$\beta^\star \approx \widetilde{\beta} - \delta(\mathring{\beta} - \widetilde{\beta})\frac{R^2_{max} - \widetilde{R}^2}{\widetilde{R}^2 - \mathring{R}^2}. \qquad (2)$$

The difference in the two coefficients ($\mathring{\beta} - \widetilde{\beta}$) is rescaled by the difference in R^2 of the two regressions and expressed in relation to the highest possible value of R^2 (R^2_{max}). The latter cannot be identified and is replaced by R^2_{max} as $min(2.2 \times \widetilde{\beta}, 1)$ (see Oster 2019), which is $R^2_{max} = 1$ in our model. δ determines the degree of proportionality between selection on observables and unobservables and is set to $\delta = 1$ or $\delta = -1$, depending on the direction of bias. For practical reasons, we focus on $\delta = -1$, as it implies an upward bias in the coefficient on the prudential filter. We also express the needed strength of omitted factors, relative to control variables, that would reduce the value of the coefficient to zero. An implausibly high value implies a low likelihood of omitted factors.

Table 7 shows the results. Columns 1 and 2 report baseline and intercept only (denoted as "Zero Model") inputs for the calculation of the bounded estimator. Column 3 reports the lower bound of the coefficient when $\delta = -1$. The value of the coefficient reduces compared with the baseline model. However, it remains relatively high and significant. It is unlikely that relevant unobservable variables were omitted from our benchmark regression. In fact, column 6 shows that the effect of omitted variables would have to be more than three times larger to reduce the coefficient of prudential filter to zero. Finally, bounded estimators (with $\delta = -1$ and $\delta = 1$) are enclosed within the confidence interval for $\widetilde{\beta}$. We conclude that it is unlikely that an omitted-variable bias affects our benchmark regression to a significant degree.

4.1.4 Propensity Score Regression

Propensity score models were developed to control for selection biases in non-experimental settings. They alleviate bias when a variable, important for selection into treatment (buffer size), is omitted from response regression.[27] They can reduce the imbalance in covariates in case of a "lack of complete overlap" and can produce a better estimate of the average treatment effect when the response to treatment is heterogeneous.

Generalization of the propensity score methods for the case of continuous treatment was introduced by Hirano and Imbens (2004). Further discussion and implementation can be found in Bia and Mattei (2008). Similar settings have been investigated by Arpino and Mealli (2011), Schuler, Chu, and Coffman (2016), Kim, Paik, and Kim (2017), or Zhou et al. (2020). None of them considers a setting such as ours. It simultaneously includes continuous treatment, hierarchically structured data (firm- and bank-level clusters), treatment assignment at a different cluster level (bank level) than the response regression (loan level) and a differences-in-differences model. We employed a Monte Carlo verification of its small sample properties to assess its suitability for a regression setting such as ours.[28]

[27] Due to perhaps being insignificant in sample data. In propensity score literature this property is called "doubly robust." It states that the propensity score model is unbiased if at least one of the two models, outcome regression or treatment assignment regression, is specified correctly.

[28] For space considerations the results and discussion are available upon request.

The propensity score model is estimated in two steps. We first estimate the probability of being "selected" into treatment (probability of being assigned a certain buffer size). We employed a top-down strategy to select regressors.[29] This model produces probability weights for "selection into treatment." Their inverses are used as regression weights in the second step when we estimate the loan growth model. Weighting creates a synthetic sample in which over-represented data are down-weighted and under-represented units are up-weighted. This delivers a sample in which confounders (included in the first-step regression) are orthogonal to the treatment. It renders regression unbiased due to those covariates included in the first step of the model.

Table 8 repeats the benchmark regression (1) and displays the results from two propensity score models 2–3. In propensity score model 2, selection into treatment is derived from the capital adequacy ratio, share of interbank loans, share of credit in the bank balance sheet, and the share of impairments. Credit in the bank balance sheet and share of impairments are not included in our benchmark model,[30] making the results reported here robust to these two confounders. We notice that the regression coefficient on capital buffer decreased to 5.4 percent but remains significant at the 10 percent level (p-value is 7.3 percent). We consider this to be the lower bound on the effect of capital buffer release on loan growth.

We also noticed that regression (2) creates an imbalance in capital adequacy ratio and credit share.[31] We now reestimate the propensity score model but only balance it for these two variables. Column 3

[29] We regressed the buffer on all regressors in the benchmark model and added additional regressors that could affect it. We then removed the least significant regressor one at a time and stopped when the remaining regressors were significant at the 10 percent level. Results remain unchanged at the 5 percent significance level. Regression results, balance plots, and correlation coefficients are available upon request.

[30] Due to being insignificant.

[31] Weighting the data with propensity score weights intends to "orthogonalize" pertinent covariates relative to the treatment variable (buffer). If successful, the correlation coefficient between buffer and covariates should approach zero. In practice, it is difficult to orthogonalize the sample for four variables simultaneously. When applying propensity score weights, capital adequacy ratio and credit share remained correlated with the buffer.

Table 8. Propensity Score Model

	(1)	(2)	(3)
Prudential Filter	0.111**	0.054*	0.084**
	(0.049)	(0.034)	(0.034)
Capital Adequacy Ratio	0.016	0.027**	0.038**
	(0.011)	(0.008)	(0.008)
Share of NPL	0.024*	0.003	0.008
	(0.013)	(0.008)	(0.008)
Total Assets	–0.000*	–0.000**	–0.000***
	(0.000)	(0.000)	(0.000)
Constant	–0.124	0.011	0.033***
	(0.146)	(0.007)	(0.007)
Firm FE	Yes	Yes	Yes
No. of Observations	11,043	11,043	11,043

Source: Bank of Slovenia, own calculations.
Note: The table reports the estimation results for the loan-level differences-in-differences model (1) and two propensity score models, (2) and (3). The dependent variable in all the equations is firm i loan growth in bank j in period 2008:Q3–2009:Q3 (10 percent is expressed as 0.1). Prudential filter is recorded at its amount in 2008:Q3 (just before the release) and expressed in percent of RWA. Capital adequacy ratio, share of NPL, and bank total assets are taken from 2008:Q3. Standard errors (in parentheses) are clustered at the bank level. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in Table 8 displays the results. The coefficient on buffer increased to 8.4 percent and was significant at the 1 percent level.

Regardless of the variables used to model selection into treatment, the effect of buffer release on loan growth is positive and statistically as well as economically significant.

5. Conclusion

This paper studies a unique experiment in the Slovenian banking system in 2007–10. The experiment is called the prudential filter and it acted like a countercyclical capital buffer. In 2008:Q4, an exogenous shock caused the prudential filter abdication. This resulted in a one-time increase of bank capital by 0.8 percent of risk-weighted assets on average. We estimate how this release of bank capital, akin to a countercyclical capital buffer, affected the banking system at the start of the financial crisis.

Our key results are the following. First, we show that banks with larger capital buffers lend more. A firm borrowing from a bank with a 1 pp higher capital buffer recorded a 5–11 pp higher credit growth, depending on the preferred model. This result is robust to various model specifications, estimation horizons, and robustness checks for omitted-variable bias. Second, healthy firms benefited the most from the excess credit capacity created by the buffer release. This intensifies the positive effect of the buffer on the real economy. Finally, we show that banks used extra loss-absorption capacity, resulting from the buffer release, to provision more for defaulted borrowers. Since a delay in loan loss recognition prolongs and intensifies the effects of financial crises, the CCyB can be considered as an effective mitigation policy.

Our findings are important for policymakers, supervisors, and regulators. We show that capital-based macroprudential measures, such as capital buffer, are an effective tool to support lending in turbulent economic conditions. In addition, they increase the loss-absorption capacity of banks. Banks use it to provision more for non-performing exposures. In light of recent policy measures taken in response to the outbreak of the COVID-19, we expect capital measures to perform well. It will be interesting to contrast our results with ex post verification of capital measures that are now being taken in response to the COVID-19 outbreak.

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