- Draft -

Do banks have an internal market for equity? Implications for cross-border spillover of policy measures*

Giuseppe Cappelletti † Aurea Ponte Marques ‡ Carmelo Salleo §

November 5, 2019

Abstract

Macroprudential policy can generate unintended cross-border spillovers, both owing to regulatory arbitrage and risk management decisions by banking groups. Banking groups that rely on subsidiaries to operate across countries might have their capital subjected to ring-fenced by host authorities who fear that if it were transferred abroad this would impact negatively the local supply of credit. However, since supervisory measures are expressed in ratios banks can at least to an extent circumvent such ring-fencing for example by reducing lending locally or reallocating it to portfolios with lower risk-weights, thus freeing up capital at the consolidated level and re-allocating it. To explicitly analyze leakages, in particular whether banks engage in such behaviour we study the impact of higher capital buffers, namely of other Systemically Important Institutions (OSII) buffers, on affiliated banks' risk-taking and credit supply, controlling for banks' characteristics such as structure and regulatory requirements. The EBA framework for OSII buffers, which is mainly determined by a cut-off rule that automatically designates banks as systemically important, allows us to study the effects of the OSIIs buffers with a difference-in-discontinuities design and a difference-in-differences estimation to verify the results. Relying on granular confidential supervisory data between 2014 and 2017, we find that when affiliated banks or their respective parent bank are constrained with an OSII buffer, banks' subsidiaries reduce their credit supply and also shift their lending to less risky counterparts in the non-financial private sector, in particular in the non-financial corporations sector.

Keywords: Macroprudential measures, Credit Supply, Bank risk-shifting, Internal capital markets

JEL Codes: E44, E51, E58, G21, G28

*Disclaimer: This paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

†European Central Bank: giuseppe.cappelletti@ecb.int
‡European Central Bank: aurea.marques@ecb.int
§European Central Bank: carmello.salleo@ecb.europa.eu

Non-Technical Summary

1 Introduction

Evidence on the effectiveness of macroprudential policy measures is still a challenge and further analytical work is this area is needed. With this paper, we contribute to the research by exploiting the European Union (EU) institutional setting for the application of Other Systemically Important Institutions (O-SIIs) buffers and assess the impact of this capital surcharge on banks' subsidiaries. Since the beginning of 2015, 108 entities were identified as O-SIIs and charged with supplementary requirements concerning the amount of Common Equity Tier 1 (CET1). Although the policy was implemented with different methodologies and different phase-in arrangements, the protocol for the identification of the O-SIIs has been established in the European Banking Authority (EBA) guidelines (EBA (2014)). Based on some mandatory indicators, each institution receives a score, which should reflect its systemic importance, and banks with a score above a certain threshold are automatically designated as O-SIIs.[1] The O-SIIs buffers are key instruments for addressing misaligned incentives and moral hazard (ESRB (2014)).

Following recent progress on data collection, a strand of literature has attempted to shed light on the link between capital regulation and economic growth. Recent studies include Shim et al. (2013), who put together a database on policy actions related to the housing markets globally and made this publicly available. Vandenbussche et al. (2012) collected information on macroprudential policy measures related to house prices in a database for 16 countries in Central, Eastern, and South-Eastern Europe at a quarterly frequency. Federico et al. (2012a) constructed a quarterly dataset on legal reserve requirements for 52 countries, of which 15 are industrial and 37 developing countries, focusing on legal rather than actual reserve requirements, for 1970-2011. The focus of most papers has been on the effects of buffer requirements on the cost of banks' capital, credit supply and risk-taking, which in turn can have an impact on the real economy.

Measuring the effects of macroprudential measures on banks 'risk taking and credit supply is far from trivial as there are many confounding factors, such as variation in bank lending due to changes in loan demand. The use of micro-data helps in addressing these factors. The main dependent variable in micro-data-based studies is generally specified as bank lending since this is the key transmission channel running from banks to the real economy (Buch and Goldberg, 2017). Using loan growth to different sectors as the dependent variable allows disentangling bank credit demand from supply (Aiyar, Calomiris, and Wieladek, 2014a and 2014b). In terms of explanatory variables reflecting changes in macroprudential policies several studies looked at changes in bank capital requirements. During the 1990s and 2000s, the Financial Services Authority (FSA) varied individual banks' minimum risk-based capital requirements for all UK-owned banks and resident foreign subsidiaries. To explicitly analyse leakages, Aiyar, Calomiris, and Wieladek (2014a)

[1] As explained later, national authorities also have the possibility to implement the supervisory judgment, generally to identify as O-SIIs banks falling below the automatic score threshold.

regress branch lending growth on lending of a reference group of regulated banks instrumented by the change in capital requirements that occurred for that reference group. When seeking to measure the effects on bank loan supply from changes in macroprudential measures, it is important to recognize, and control for bank characteristics, loan demand as well as country characteristics. Aiyar, Calomiris, and Wieladek (2014a and 2014b) use employment growth rate at quarterly frequency for each of the economic sectors analysed to control for bank credit demand. Aiyar et al. (2014), Mosk et al. (2016) and Gropp et al. (2016) find that banks constrained with higher capital requirements tend to increase their capital ratios not by raising their levels of equity, but by reducing their credit supply. Noss and Toffano (2014) suggest that an increase of 15 basis points in aggregate capital ratios of banks operating in the UK is associated with a median reduction of around 1.4 percent in the level of lending after 16 quarters. Becker et al. (2014) find strong evidence of the substitution from loans to bonds as a contraction in bank-credit supply at times that are characterized by tight lending standards, depressed aggregate lending and tight monetary policy. Bridges et al. (2014) show that in the year following an increase in capital requirements, banks, on average, cut (in descending order based on point estimates) loan growth for commercial real estate, other corporates and household secured lending. Yet, loan growth mostly recovers within three years. Following the same results, Martynova (2015) suggests that banks facing higher capital requirements can reduce credit supply as well as decrease credit demand by raising lending rates which may slow down economic growth. However, having better capitalized banks enhances financial stability by reducing bank risk-taking incentives and increasing banks' buffers against losses. Buch and Prieto (2014) find no evidence for a negative impact of bank capital on business loans in Germany. Although the theoretical literature indeed suggests that this may be the case, existing empirical evidence does not reach a consensus in evaluating the short-term response of credit supply to increased capital requirements, with the magnitude and the sign of the effect being highly dependent on institutional factors. Adequate phase-in arrangements, for instance, may allow banks to smoothly adjust their balance sheets, thereby limiting possible backlashes of tighter restrictions on the real economy. In the case of the O-SII institutional framework, the activation of the buffer requirement was generally phased-in over several years, which may provide a rationale for the absence of short-term effects on the volume of credit.

In contrast to the hypothesis that moral hazard costs amplify risk-taking [2], some literature suggests that regulatory surcharges had a positive disciplining effect. This is in line with some strands of the theoretical literature on the impact of capital based regulation on risk-taking, which however is largely ambiguous.

[2] The recent crisis showed that certain financial institutions are too systemically important to fail, which may lead to misaligned incentives and greater moral hazard (ESRB (2015)). Shocks to these systemically important institutions (SIIs) may give rise to losses and liquidity shortages in the rest of the financial system, both through direct and indirect channels. O-SIIs are institutions that, due to their systemic importance, are more likely to create risks to financial stability and the real economy.

Furlong and Keeley (1989), for instance, incorporate the option-value of deposit insurance into a state-preference model and show that a value-maximizing risk-neutral bank responds to an exogenous increase in bank capital by reducing the level of riskier assets. This conclusion, however, is reversed once risk aversion is considered.

Our paper contributes to two strands of literature. First, it relates to the empirical literature in which the effect of capital policy regulation using granular bank-level data is analyzed. Second, the paper relates to the literature on the cross-border spillover effects of macroprudential policy actions on banks' risk-taking and lending. The remaining of the paper is organized as follows. Section 2 describes the dataset and the process for the identification of the O-SIIs, as established in the EBA guidelines, while Section 3 explains the identification strategy and lays out the results. Section 5 concludes.

2 Data and O-SIIs framework

Our analysis relies mainly on confidential granular supervisory data, which is quarterly reported for Euro Area banks, between 2014:Q4 and 2017:Q4, and includes information on volumes of exposures, risk-weighted assets, impairments or expected losses, as well as indicators of capital, such as CET1. In addition, an internal dataset on O-SIIs is used, which includes for example the level of required capital buffer and the date of notification for the O-SII assessment. Complementing confidential supervisory data with the information provided by national authorities, we are able to estimate the overall score of 372 banks from 17 Euro Area countries and their distance from the threshold for the automatic identification.[3] Out of 372 entities, 107 were identified as O-SIIs, the vast majority of which qualifies as Significant Institutions (SI) or subsidiaries in other Member States. In addition, the group of O-SIIs includes 7 Less Significant Institutions (LSIs) and one institution (an export corporation in Slovenia) which is neither SI nor LSI.

In terms of O-SIIs identification framework, under Article 131(3) of the Directive 2013/36/EU ('CRD IV'), the EBA Guidelines (EBA/GL/2014/10) established a two-step procedure for identifying O-SIIs.[4] In the first step, the national authorities calculate a score for each relevant entity, at least at the highest level of consolidation of the banking group under their jurisdiction. The scoring process, established in the guidelines, is based on mandatory indicators that should capture the systemic footprint of each institution (see Table 1). A bank is then designated as O-SII if its score is equal to or higher than 350 basis points. Taking into account the specificities of the Member State's banking sector and the resulting statistical distribution of scores, relevant authorities may raise this threshold up to 425 basis points or decrease it to 275 basis points,

[3]The relevant threshold considered depends on the home country of the reporting bank.

[4]Although the EBA guidance is not compulsory, almost all countries follow these guidelines Yet, some believe that the strict application of the EBA protocol does not properly reflect countries' specificities, which may be relevant for the identification of the O-SIIs.

Table 1: O-SII scoring: indicators and criterion (EBA, 2014).

Size	Total assets
Importance (including substitutability/financial system infrastructure)	Value of domestic payment transactions
	Private sector deposits from depositors in the EU
	Private sector loans to recipients in the EU
Complexity/cross-border activity	Value of OTC derivatives (notional)
	Cross-jurisdictional liabilities
	Cross-jurisdictional claims
Interconnectedness	Intra-financial system liabilities
	Intra-financial system assets
	Debt securities outstanding

so as to ensure the homogeneity of the group of O-SIIs that results from the automatic calculation.

The second step of the procedure entails a supervisory overlay, whereby it is assessed whether further institutions are systemically relevant in order to be also qualified as O-SIIs. To conduct the assessment, relevant authorities select the indicators considered adequate in capturing systemic risk in their domestic sector or in the economy of the Union.[5] Supervisory judgment is typically applied to identify institutions as O-SIIs banks which fall under the automatic score.[6] From 1 January 2016, designated entities started to implement stricter capital requirements, typically in the form of CET1 capital buffers.[7] As the EBA guidelines do not provide any guidance on how the O-SII buffer should be calibrated, EU countries have used various methods, and sometimes additional indicators, for the calibration of O-SII buffers.[8] The EU legislation, however, provides some constrains: a cap limit of O-SIIs of 2 percent, and for subsidiaries the additional capital requirement cannot exceed the higher between 1 percent and the Global Systemically Important Institutions (G-SIIs) or O-SIIs buffer applicable to the group at the consolidated level.

As the calibration of the buffer, the timing of the introduction of the measure is also quite heterogeneous. There is considerable variation in the first year of implementation of the policy measure, where several

[5] Moreover, according to the EBA guidelines, consistent with the Basel Committee on Banking Supervision (BCBS) framework for domestic systemically important banks, relevant authorities should publicly disclose information on the outline of the methodology applied to assess systemic importance.

[6] However, institutions with a score not exceeding 4.5 basis points should not be designated as O-SIIs.

[7] In few countries (Estonia, the Netherlands and Slovakia) the O-SII surcharge was complemented with the introduction of the Systemic Risk Buffer.

[8] For instance, together with the score computed for the identification, they have considered banks' systemic importance as measured by their size, lending activity and other optional indicators such as historical losses and the gross domestic product.

countries decided to defer the start of the execution of a positive O-SII capital surcharge beyond 2016.[9] In addition, different multi-year linear phase-in periods have been adopted, with Estonia, Finland, Lithuania and Slovenia being the only countries that required fully loaded implementation already from the first year.

To identify how banks adjust their balance sheets in response to higher capital buffer requirements, i.e. to estimate the causal impact of O-SIIs on banks' credit supply and risk-taking behaviour, we consider different indicators; all of them computed using the exposure at default (EAD) as a measure of total exposures.[10] To quantify changes in levels of lending, we calculate the quarterly credit growth rate by using the bank's credit flow, where the flow is computed as the quarterly variation in exposures plus the redemption, i.e.: $Credit\ Flow_t = (Exposures\ at\ Default_t - Exposures\ at\ Default_{t-1}) + Redemptions_t$

To assess risk-taking, we employ two main indicators, namely: the average risk-weights or risk-weighted assets density and the average global charge.[11] The average risk-weights, defined as the ratio of risk-weighted assets to total exposures, is widely used to measure the average risk relative to the exposures taken by a bank. For standard approach (STA) exposures the risk-weights are defined according external ratings or level of collateralization, as detailed in the Regulation (EU) No 575/2013 ('CRR'). The global charge, by contrast, is a more comprehensive measure of the riskiness of exposures since it includes both expected and unexpected losses. This indicator is computed for IRB exposures as: and for STA exposures as: In Table 2 we present for each variable of interest the mean and the standard deviation, separately for the group of banks below and above the threshold before and after the identification.

[9] The countries that delayed the activation of the buffer beyond 2016 were Cyprus, Germany, Ireland, Greece, Lithuania, Portugal and Slovenia.

[10] Exposures are also analyzed in order to assess other events, such as the increase of exposures to sovereign debt (Becker and Ivashina (2014); Ongena, Popov, and Van Horen (2016)) as a consequence, for example, of the ECB's longer-term refinancing operations (LTRO) program (Van Rixtel and Gasperini (2013)). The EAD might be considered as a measure of size, which includes both on-balance-sheet assets and off-balance-sheet contingent exposures and commitments (converted into equivalent on-balance-sheet amounts through the application of credit conversion factors).

[11] This indicator is broadly used by the EBA in their annual review of RWA's variability (see https://www.eba.europa.eu/-/eba-interim-report-on-the-consistency-of-risk-weighted-assets-in-the-banking-book).

Table 2: Descriptive Statistics

	Banks below the threshold		Banks above the threshold	
	Pre-notification	Post-notification	Pre-notification	Post-notification
Panel A: Δ Avg. Risk-Weights				
Households	-0.001	-0.001	-0.014	-0.002
	(0.011)	(0.012)	(1.429)	(0.059)
Non-financial corporations	-0.029	0.010	-0.002	0.001
	(0.178)	(0.067)	(0.066)	(0.126)
Non-financial private sector	-0.005	0.004	-0.003	-0.001
	(0.021)	(0.020)	(0.097)	(0.061)
Financial sector	-0.016	-0.005	-0.005	-0.001
	(0.071)	(0.018)	(0.010)	(0.059)
Public Sector	-0.001	0.000	-0.001	-0.002
	(0.005)	(0.008)	(0.083)	(0.003)
Panel B: Δ Avg. Global Charge				
Households	-0.010	0.001	0.009	-0.002
	(0.039)	(0.030)	(2.391)	(0.432)
Non-financial corporations	-0.030	0.003	0.002	-0.007
	(0.180)	(0.072)	(0.187)	(0.123)
Non-financial private sector	-0.002	-0.002	-0.004	-0.003
	(0.036)	(0.040)	(1.75)	(0.488)
Financial sector	-0.017	-0.005	-0.014	0.007
	(0.071)	(0.018)	(0.625)	(0.364)
Public sector	-0.001	0.000	-0.039	0.043
	(0.005)	(0.008)	(5.123)	(3.343)
Panel C: Δ(%) Credit Growth				
Households	-0.010	0.000	0.343	0.215
	(0.147)	(0.165)	(10.858)	(6.760)
Non-financial corporations	0.075	0.038	2.507	2.251
	(0.098)	(0.209)	(133.89)	(146.845)
Non-financial private sector	0.108	0.223	4.873	59.060
	(0.204)	(0.458)	(113.063)	(2673.635)
Financial sector	0.093	0.047	2.066	26.210
	(0.284)	(0.216)	(90.485)	(1358.003)
Public sector	0.050	0.038	183.592	2.013
	(0.096)	(0.202)	(13312.47)	(97.442)

Notes: Data between 2014:Q4 and 2017:Q4. Mean values are computed separately for banks below and above the threshold, as well as before and after the notification of the O-SII assessment. Standard deviations are reported in parenthesis. The quarterly percentage change in credit growth, average risk-weights and global charges are in percentage points.

3 Econometric setup

This study relies on a peculiarity of the institutional framework discussed above, namely the fact that the identification of the O-SIIs and the application of the related capital buffer are based on predetermined thresholds. As anticipated in the previous section, EBA's guidelines on the identification of O-SIIs establish a scoring process for the assessment of an institution's systemic importance based on four mandatory indicators: size, importance, complexity/cross-border activity and interconnectedness. Taking into account these criteria, national authorities assign to each bank under their jurisdiction a score that should represent its systemic footprint within each national banking system. Crucially, institutions with a score equal to or higher than a certain threshold are automatically identified as O-SIIs.

Although the automatic calculation is often complemented with supervisory judgment, the O-SII framework provides a natural setting for a difference-in-discontinuities design (diff-in-disc).[12] The key underlying assumption is that there exists a narrow window around the threshold such that for all banks whose scores fall in that window, the placement above or below the cutoff is assigned as in a randomized experiment.[13] If the EBA assessment protocol indeed induces a randomized experiment in a neighbourhood of the threshold, it is possible to identify the effect of higher capital requirements by comparing the change in the outcome of banks just above and below the cutoff, before and after the introduction of the additional surcharge.[14]Also, in order to validate the results obtained from the diff-in-disc a difference-in-differences method is performed

3.1 Identification Strategy

In terms of identification strategy, a random sample of N banks was considered, indexed by $i = 1,...,N$, which are followed for T time periods, indexed by $t = 1,...,T$. Let I_{itc} be the (binary) treatment status for bank i in country c at time t. In our context, $I_{itc} = 1$ if the bank is identified as O-SII and $I_{itc} = 0$ otherwise. We are interested in studying the effect of I_{itc} on some policy outcome Y_{itc}. Let us denote $Y_{itc}(0)$ and $Y_{itc}(1)$ the potential outcomes. Then, for each bank i in the sample, the observed outcome is given by:

[12]These designs were first introduced in the evaluation literature by Thistlethwaite and Campbell (1960). Leonardi and Pica (2013) apply a diff-in-disc approach to study the effect of employment protection legislation on wages. Grembi et al. (2016) investigate the impact of relaxing fiscal rules on a wide array of outcomes. Imbens (2008) use the RD designs for evaluating causal effects of interventions, assignment to a treatment is determined at least partly by the value of an observed covariate lying on either side of a fixed threshold.

[13]The original motivation for a local randomization approach was given by Lee (2008), and has been bolstered by several studies showing that regression discontinuity designs can recover experimental benchmarks (e.g. Green et al. (2009); Calonico et al. (2014a, 2014b, 2015 and 2016)). Based on Cattaneo et al. (2015, 2016, 2017a and 2017b), the underlying assumption is that the treatment assignment is probabilistic and unrelated to the potential outcomes in a window around the cutoff, and the potential outcomes are allowed to depend directly on the score.

[14]There is considerable heterogeneity in the level of the additional requirement. In the neighbourhood of the cutoff score, however, the surcharges are generally low, which possibly makes more difficult to detect a sizable effect of the regulatory change.

$$Y_{itc} = \begin{cases} Y_{itc}(0) & \text{if } I_{itc} = 0 \\ Y_{itc}(1) & \text{if } I_{itc} = 1 \end{cases}$$

At any time t and for each bank i, we observe a score, S_{itc}, which is assumed not to be affected by the treatment. After the notification is issued (i.e. for $t \geq t_{0,c}$), the treatment status I_{itc} changes with a threshold, as banks with a score above a predetermined, country-specific cutoff, S_c, are qualified as O-SIIs and charged with an additional capital requirement.[15] If the outcome of the identification process depended only on this automatic calculation we would have:

$$I_{itc} = \begin{cases} 1 \text{ if } S_{itc} \geq S_c \text{ and } t \geq t_{0,c} \\ 0 \text{ otherwise} \end{cases}$$

However, following supervisory judgment, some banks may be deemed so systemically relevant to be designated as O-SIIs even if their score is below S_c. This implies that the probability of assignment to the treatment changes discontinuously at the threshold but does not jump from 0 to 1, leading to a fuzzy regression discontinuity design (RDD) setting:

$$\lim_{\varepsilon \to 0^+} \Pr(I_{itc} = 1 | S_{itc} = S_c + \varepsilon, t \geq t_{0,c}) > \lim_{\varepsilon \to 0^-} \Pr(I_{itc} = 0 | S_{itc} = S_c + \varepsilon, t \geq t_{0,c})$$

In this setup, one could take advantage of the discontinuous change in treatment assignment at the threshold to measure the causal impact of the treatment on the outcomes of interest. Following Hahn et al. (2001), let $Y^+ = \lim_{\varepsilon \to 0^+} E[Y_{itc} | \, S_{itc} = S_c + \varepsilon, \, t \geq t_{0,c}]$ and $Y^- = \lim_{\varepsilon \to 0^-} E[Y_{itc} | \, S_{itc} = S_c + \varepsilon, t \geq t_{0,c}]$. The analogous expressions for the treatment status are $I^+ = \lim_{\varepsilon \to 0^+} E[I_{itc} | \, S_{itc} = S_c + \varepsilon, \, t \geq t_{0,c}]$ and $I^- = \lim_{\varepsilon \to 0^-} E[I_{itc} | \, S_{itc} = S_c + \varepsilon, \, t \geq t_{0,c}]$. In the standard RDD setting, the treatment effect is given by

$$\tau_{FRD} = \frac{Y^+ - Y^-}{I^+ - I^-}$$

Our "difference-in-discontinuities" approach departs from a conventional RDD strategy in that it exploits an additional source of variation, namely the policy change after $t_{0,c}$. Letting $\tilde{Y}^+ = \lim_{\varepsilon \to 0^+} E[Y_{itc} | \, S_{itc} = S_c + \varepsilon, \, t < t_{0,c}]$ and $\tilde{Y}^- = \lim_{\varepsilon \to 0^-} E[Y_{itc} | \, S_{itc} = S_c + \varepsilon, \, t < t_{0,c}]$, the treatment effect of I_{itc} on Y_{itc} can be written as

[15] It should be noted that the introduction of the O-SII capital buffers has been often postponed in time and phased-in over several time periods. However, it is plausible that banks started adjusting their balance sheets as soon as they were identified as systemic institutions. We therefore regard the adjustment period as starting just after the notifications have been issued by the national authorities.

$$\tau_{FDD} = \frac{(Y^+ - Y^-) - (\tilde{Y}^+ - \tilde{Y}^-)}{I^+ - I^-}$$

Assuming that all potential outcomes are continuous in S at the threshold and that observation just above and just below S_c are on a local parallel trend in the absence of the policy, the ratio τ_{FDD} identifies the local average treatment effect of being designated as O-SII on the outcome of interest. Depending on the framework, the specifications are estimated using different set of fixed-effects: time-invariant bank characteristics, and country-specific fixed effects that should capture time-invariant country traits. Time varying bank-specific characteristics, such as CET1 and an indicator variable that captures whether the bank is a subsidiary of a foreign bank are included.

The characteristic of the O-SII institutional framework provides us with an ideal ground to assess the impact of higher capital requirements on banks' lending behaviour.[16] Exploiting the discontinuity induced by the EBA selection rule, allows us to explore the impact of increased capital restrictions on credit growth and risk-taking with a diff-in-disc (or a diff-in-diff) by employing a modified version of Leonardi and Pica (2013) and Grembi et al. (2016) design. This strategy causally identifies the effect of the regulatory shock by comparing the change in the outcomes of interest for banks just above and below the cutoff, i.e. before and after the introduction of the additional capital surcharge.

3.2 Estimation

To perform the estimation, a nonparametric approach was implemented, which fits a flexible functional form to observations distributed within a distance h on both sides of the cutoff score, S_c.(Lee and Lemieux (2008 and 2010) and Gelman and Imbens (2014)) The reduced-form specification is

$$Y_{itc} = \beta_0 + \beta_1 OSII_{itc} + \beta_2 (OSII_{itc} \cdot Post_{tc}) + f(S_{itc} - S_c) + \gamma \cdot X_{itc} + \epsilon_{itc}$$

where $OSII_{itc}$ is a dummy that takes value 1 if bank i in country c has been identified as O-SII and 0 otherwise, $S_{itc} - S_c$ is the bank's normalized score and $Post_{tc}$ is a dummy that equals 1 after the adoption of the capital buffer; u_t are quarter fixed effects; η_c are country fixed effects; and ϵ_{it} is the individual error term. The X_{itc} are a series of control variables, namely the bank's CET1, the credit-to-GDP gap and a dummy variable that takes the value 1 if the parent bank has been constrained with an O-SII buffer. To further identify the effect of the additional capital surcharge, we rule out the possibility that our results may be driven by the (aggregate) credit cycle. To this purpose, we include in our baseline regression the

[16] Banks can increase their capital ratios in two different ways: they can either increase their levels of own funds (the numerator of the capital ratio) or they can dampen down their risk-weighted assets (the denominator of the capital ratio) (Gropp et al (2016)). Our analysis is focused on the denominator of the capital ratio in order to assess banks' lending behaviour.

credit-to-GDP gap, defined as the difference of credit-to-GDP from its long-run trend in percentage points. Adding an indicator of the financial cycle to our fixed effect specification allows us to better control for observed and unobserved time-varying heterogeneity at the country level.

If the O-SII assessment were based solely on the banks' individual scores, the OLS estimation of the above regression function for banks with a score in the interval $[S_c - h; S_c + h]$ would allow us to identify the effect of interest. In fact, the identification process of the O-SIIs is partly determined by factors other than the banks' score, because of supervisory overlay. As a consequence, banks with a score below the threshold may nevertheless be identified as O-SIIs and be subject to the related capital requirement. This leads to a fuzzy discontinuity in the application of the O-SII buffer that needs to be accounted for. To this purpose, we instrument $OSII_{itc}$ and $OSII_{itc} \cdot Post_{tc}$, using respectively D_{itc} and $D_{itc} \cdot Post_{tc}$, where D_{itc} is a dummy that takes value 1 if the score of bank i at time t is above the threshold S_c, and 0 otherwise. Formally, we restrict the sample to banks with a score in the interval $[S_c + h; S_c + h]$ and implement the following IV specification:

$$Y_{itc} = \beta_0 + \beta_1 OSII_{itc} + \beta_2 (OSII_{itc} \cdot Post_{tc}) + f(S_{itc} - S_c) + \gamma \cdot X_{itc} + \epsilon_{itc}$$

$$OSII_{itc} = \delta_0 + \delta_1 D_{itc} + \delta_2 (D_{itc} \cdot Post_{tc}) + f(S_{itc} - S_c) + \gamma \cdot X_{itc} + \epsilon_{itc}$$

$$OSII_{itc} \cdot Post_{tc} = \zeta_0 + \zeta_1 D_{itc} + \zeta_2 (D_{itc} \cdot Post_{tc}) + f(S_{itc} - S_c) + \gamma \cdot X_{itc} + \epsilon_{itc}$$

The coefficient β_2 on the interaction term $OSII_{itc} \cdot Post_{tc}$ between the O-SII dummy and the post-notification dummy is the diff-in-disc estimator and identifies the effect of being designated as O-SII on the outcome of interest, Y_{itc}. As in standard IV exercises, identification relies on the exclusion restriction, according to which the instruments must not affect the outcome but through their effects on the instrumented variables. In our baseline specification we estimate the local average treatment effect (LATE) through local linear regressions with a triangular kernel, fitting a polynomial of order one in $(S_{itc} - S_c)$ on either side of the threshold:

$$Y_{itc} = \beta_0 + \beta_1 OSII_{itc} + \beta_2 (OSII_{itc} \cdot Post_{tc}) + \gamma_0 (S_{itc} - S_c) + \gamma_1 (S_{itc} - S_c) D_{itc} + \gamma \cdot X_{itc} + \epsilon_{itc}$$

$$OSII_{itc} = \delta_0 + \delta_1 D_{itc} + \delta_2 (D_{itc} \cdot Post_{tc}) + \delta_3 (S_{itc} - S_c) + \delta_4 (S_{itc} - S_c) D_{itc} + \gamma \cdot X_{itc} + \epsilon_{itc}$$

$$OSII_{itc} \cdot Post_{tc} = \zeta_0 + \zeta_1 D_{itc} + \zeta_2 (D_{itc} \cdot Post_{t}) + \zeta_3 (S_{itc} - S_c) + \zeta_4 (S_{itc} - S_c) D_{itc} + \gamma \cdot X_{itc} + \epsilon_{itc}$$

All regressions include quarter fixed effect and country fixed effect, to control for macro shock that may affect a bank's risk-taking behaviour. Accordingly, the reported standard errors account for possible error correlation at the country level. We establish the robustness of our results to multiple bandwidths h, by presenting the diff-in-disc estimates for both the mean-squared-error (MSE) optimal and the coverage-error-rate (CER) optimal bandwidths developed by Calonico et al. (2016).[17]

By implementing the framework discussed beforehand, capital surcharges are applied to banks identified as O-SIIs based on predetermined thresholds. As such, it allows to exploit the exogenous variation of capital requirements and its consequent cross-sectional and time variability when analyzing banks' risk taking and credit supply to the real economy. With that in mind, the implementation of this measure is treated as a quasi-natural experiment allowing for the application of a diff-in-diff design. For that the following regression using OLS is estimated:

$$Y_{itc} = \beta_0 + \beta_1 OSII_{itc} + \beta_2 Post_{tc} + \beta_3 (OSII_{itc} \cdot Post_{tc}) + \gamma \cdot X_{itc} + \eta_{ct} + \epsilon_{itc}$$

where X_{itc} is the bank's CET1 level. η_{ct} are quarter and country specific fixed-effects and $\epsilon_{i,t,c}$ is the individual error term. The underlying assumption is that by focusing on banks' subsidiaries and controlling for pre-treatment characteristics, through the $OSII_{it}$ dummy, as well as for post-treatment trend, no additional terms are considered confounding variables that bias the results. Moreover, the capital control implemented accounts for the heterogeneity of the policy measure and, with the dummy variable for financial group structures, any change in trend after the treatment is controlled.

3.3 Results

The probability of being designated as O-SII increases significantly and discontinuously if a bank receives a score above the automatic cutoff. Not surprisingly, the percentage of banks on the right of the threshold that are designated as O-SIIs is almost equal to one, as these banks should be automatically qualified as systemically important. By contrast, several institutions below the cutoff are, nevertheless, designated as O-SIIs because of supervisory judgment[18]. Therefore, the use of a fuzzy design is appropriate for the setting at hand. The diff-in-disc estimates from our baseline specification are reported in Tables 3 and 4, which respectively present the results for credit growth and risk-taking. The dependent variable in Table 3 is the quarterly percentage change in the credit growth. In Panel A of Table 4 it is the change in the average risk-weights or risk-weighted assets density and in Panel B it is the change in the average global charge.

[17] Optimal bandwidth choice was also analyzed by Imbens et al. (2012).

[18] Six countries (Belgium, Estonia, Germany, France, Malta and the Netherlands) complemented the automatic calculation for the identification of the O-SIIs with supervisory judgment.

Table 3: Credit Growth: Average Effect of O-SII Buffer Requirement

	Households	Non-financial corporations	Non-financial private sector	Financial sector	Public sector
Δ(%) Credit Flows					
MSE-optimal bandwidth	-0.025	-0.105**	-0.153*	-0.130	-0.027
	(0.018)	(0.033)	(0.074)	(0.069)	(0.056)
Observations	176	96	100	103	100
First-stage F-statistic	698.0	328.2	417.6	474.8	336.4
Sanderson-Windmeijer F-statistic	794.4	311.9	313.2	348.1	282.6
CER-optimal bandwidth	-0.025	-0.089*	-0.168*	-0.154	-0.039
	(0.017)	(0.044)	(0.076)	(0.087)	(0.062)
Observations	154	72	87	89	82
First-stage F-statistic	698.5	215.6	266.7	296.3	246.8
Sanderson-Windmeijer F-statistic	723.6	84.68	168.1	252.5	125.7

Notes: Diff-in-disc estimates for the effect of O-SII identification on credit growth. The dependent variable is the quarterly percentage change in credit growth We perform local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. All regressions include quarter fixed effects, country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 1.99^{th} percentile. Furthermore, only banks with a CET1 close (75% closest) to 10.5% are considered. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Data is aggregated into four categories - households, non-financial corporations, non-financial private sector, financial sector and public sector - so as to identify the effect of the regulatory surcharge on each sector of the economy. Furthermore, each outcome variable is trimmed at the 1 percent level to reduce the influence of extreme values on the precision of the estimates. In each table we only show the coefficient on the interaction between the O-SII dummy and the post-notification dummy, along with the corresponding first-stage statistics. We report, in particular, the standard F-statistic for the test of the excluded instruments, as well as the Sanderson-Windmeijer F-statistic which accounts for the presence of multiple endogenous regressors (Sanderson and Windmeijer (2015)).

We find that banks' subsidiaries (or respective Parent) constrained with a O-SIIs buffer reduce their lending and also shifted their credit to less risky counterparts in the non-financial private sector, in particular in the non-financial corporations sector, given that the coefficients reported in Table 3 and Table 4 are statistically significant. Quantitatively, the estimates reported in Table 4 imply that banks just above the threshold reduced the average global charge and lending on the non-financial corporations sector by approximately 0.1 points more than banks just below the cutoff, after being identified as O-SIIs.

For an additional verification of the results, the diff-in-diff estimates are reported in 5 and 6, which

Table 4: Risk Taking: Average Effect of O-SII Buffer Requirement

	Households	Non-financial corporations	Non-financial private sector	Financial sector	Public sector
Panel A: Δ Avg. Risk-Weights					
MSE-optimal bandwidth	-0.009	0.004	0.001	0.032	0.006
	(0.005)	(0.009)	(0.005)	(0.021)	(0.006)
Observations	154	128	133	134	151
First-stage F-statistic	697.6	548.3	638.4	661.5	684.4
Sanderson-Windmeijer F-statistic	716.2	420.4	460.2	500.0	653.1
CER-optimal bandwidth	-0.010	0.009	0.002	0.044*	0.005
	(0.006)	(0.009)	(0.007)	(0.021)	(0.006)
Observations	133	103	107	120	132
First-stage F-statistic	638.2	435.5	483.2	503.5	618.0
Sanderson-Windmeijer F-statistic	461.9	321.3	360.3	398.8	449.3
Panel B: Δ Avg. Global Charge					
MSE-optimal bandwidth	-0.005	-0.092*	-0.024	0.027	0.008
	(0.007)	(0.037)	(0.045)	(0.020)	(0.005)
Observations	134	150	134	134	173
First-stage F-statistic	655.3	685.0	663.2	656.1	691.8
Sanderson-Windmeijer F-statistic	489.3	609.6	503.6	490.5	809.2
CER-optimal bandwidth	0.000	-0.108*	-0.027	0.039	0.008
	(0.008)	(0.043)	(0.051)	(0.022)	(0.005)
Observations	120	128	120	120	150
First-stage F-statistic	496.3	583.3	505.9	497.0	685.2
Sanderson-Windmeijer F-statistic	396.1	434.3	400.9	396.1	614.8

Notes: Diff-in-disc estimates for the effect of O-SII identification on risk taking. The dependent variable in Panel A is the quarterly change in the average risk-weight, and in Panel B is the quarterly change in the average global charge. We perform local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. All regressions include quarter fixed effects, country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 1.99$^{\text{th}}$ percentile. Furthermore, only banks with a CET1 close (75% closest) to 10.5% are considered. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

present the results for credit growth and risk-taking, respectively The dependent variable in 5 Panel A is the quarter change in the average risk-weights and in Panel B it is the change in the average global charges. Data is aggregated into five sectors as mentioned above in the diff-in-disc design. Furthermore, each variable is trimmed at a 1 percent level to reduce the influence of extreme values on the precision of the estimates. In each table below, only the coefficients on O-SII dummy, the post-notification dummy and the interaction between the O-SII dummy and the post-notification dummy are presented.

The results on banks' subsidiaries show a significant effect of being identified as O-SII on banks' credit

Table 5: Credit Growth: Average Effect of O-SII Buffer Requirement

	Households	Non-financial corporations	Non-financial private sector	Financial sector	Public sector
Δ(%) Credit Growth					
Dummy O-SIi	-0.010	0.042***	0.003	-0.042**	-0.054
	(0.007)	(0.013)	(0.008)	(0.022)	(0.036)
Dummy Post	-0.017**	-0.014	-0.006	-0.286	0.005
	(0.010)	(0.015)	(0.014)	(0.084)	(0.041)
Dummy O-SIIs & Post	0.026***	-0.052***	0.009	-0.004	0.031
	(0.010)	(0.015)	(0.014)	(0.084)	(0.041)
Observations	8,114	8,601	8,829	8,633	8,685
R-Squared	0.056	0.061	0.051	0.057	0.058

Notes: Diff-in-diff estimates for the effect of the ultimate parent's O-SII identification on bank lending by its subsidiaries. The dependent variable is the quarterly percentual change in credit growth. All regressions include interaction fixed effects, i.e., by quarter and country, an intercept and CET1 as control variable. Standard errors are clustered at bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

supply for non-financial corporations, given that the coefficients reported in Table 5 are statistically significant. In addition, focusing on the banks' risk taking behaviour, the change in the average risk-weight is also statistically significant for the non-financial private sector, in particular for households and non-financial corporations

Overall, the results of both designs are aligned, i.e. we find that banks' subsidiaries (or respective Parent) constrained with a O-SIIs buffer reduce their credit supply and also shifted their lending to less risky counterparts in the non-financial private sector, in particular in the non-financial corporations sector

Table 6: Risk Taking: Average Effect of O-SII Buffer Requirement

	Households	Non-financial corporations	Non-financial private sector	Financial sector	Public sector
Panel A: Δ Avg. Risk-Weights					
Dummy O-SII	0.001*	0.002	0.001	-0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Dummy Post	-0.000	-0.000	-0.011	-0.002	-0.001
	(0.001)	(0.001)	(0.012)	(0.002)	(0.001)
Dummy O-SIIs & Post	-0.002**	-0.002	-0.013	0.006	0.001
	(0.001)	(0.002)	(0.010)	(0.003)	(0.002)
Observations	8,143	8,617	8,854	8,439	7,845
R-Squared	0.035	0.080	0.020	0.079	0.057
Panel B: Δ Avg. Global Charge					
Dummy O-SII	-0.001	0.001	0.008	-0.004	-0.002
	(0.002)	(0.004)	(0.005)	(0.004)	(0.002)
Dummy Post	0.004	0.003	-0.007	0.004	0.001
	(0.003)	(0.004)	(0.011)	(0.003)	(0.001)
Dummy O-SIIs & Post	-0.001	-0.000	-0.023*	0.004	0.001
	(0.003)	(0.006)	(0.012)	(0.005)	(0.002)
Observations	8,127	8,633	8,867	8,674	8,684
R-Squared	0.084	0.165	0.023	0.056	0.132

Notes: Diff-in-diff estimates for the effect of the ultimate parent's O-SII identification on risk taking and bank lending by its subsidiaries. The dependent variable in Panel A is the quarterly change in the average risk-weight and Panel B the quarterly change in the average global charge. All regressions include interaction fixed effects, i.e., by quarter and country, an intercept and CET1 as control variable. Standard errors are clustered at bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

4 Conclusions

In this paper, we exploit the provision of the EBA framework on the criteria for the assessment of O-SIIs to causally identify the effect of higher capital buffer requirements on banks' lending and risk-taking behaviour. According to the EBA framework, the identification of the O-SIIs is mainly determined by a scoring process, which automatically qualifies a bank with a score above a predetermined threshold as systemically important. The EBA scoring process induces for a randomized experiment in a neighbourhood of the threshold, therefore allowing to identify the effect of higher capital requirements by comparing the change in the outcome of banks just above and below the cutoff, before and after the introduction of the additional surcharge. Therefore, this framework allowed us to implement both the diff-in-disc and the diff-in-diff designs, which exploits both the regulatory change and the discontinuity induced by the O-SII identification process.

We find that O-SIIs banks' subsidiaries close to the threshold reduced their credit supply and also shifted their lending to less risky counterparts in the non-financial private sector, in particular in the non-financial corporations Therefore, and following the conclusions of Admati et al. (2015), our results suggest that banks tend to comply with higher capital requirements by dampen down their risk-weighted assets (the denominator of the capital ratio) and also by decreasing the credit supply to more risky sectors. In terms of policy implications, our results show that measures which target capital buffers could have potentially a positive disciplining effect by reducing risk-taking (see Gersbach and Rochet (2012)), while having also an adverse impact on the real economy.

References

[1] Admati, A., De Marzo, P., Hellwig, M. and Pfleiderer, P. (2015). The Leverage Ratchet Effect. *Research Papers* 3435, Stanford University, Graduate School of Business.

[2] Adrian, T and Shin, H. (2008). Financial intermediaries, financial stability, and monetary policy. *Staff Reports* 346, Federal Reserve Bank of New York.

[3] Adrian, T and Shin, H. (2009). Money, liquidity, and monetary policy. *American Economic Review: Papers and Proceedings* 99: 600-605.

[4] Adrian, T. and Shin, H. (2010a). Financial intermediaries and monetary policy. *Staff Report No.* 398, Federal Reserve Bank of New York.

[5] Adrian, T. and Shin, H. (2010b). The changing nature of financial intermediation and the financial crisis of 2007-2009. *Annual Review of Economics* 2: 603-618.

[6] Aiyar, S., Calomiris, W. and Wieladek, T. (2014). Does Macro-Prudential Regulation Leak? Evidence from a UK Policy Experiment. *Journal of Money, Credit and Banking* 46(1): 181-214.

[7] Auer, R. and Tille, C. (2016). The banking sector and the Swiss financial account during the financial and European debt crises. *Aussenwirtschaft, University of St. Gallen, School of Economics and Political Science, Swiss Institute for International Economics and Applied Economics Research* 67(02): 69-97.

[8] Becker, B. and Ivashina, V. (2014). Cyclicality of credit supply: Firm level evidence. *Journal of Monetary Economics* 62(C): 76-93.

[9] Borio, C and Zhu, H. (2008). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism? *BIS Working paper* 268.

[10] Bridges, J., Gregory, D., Nielsen, M., Pezzini, S., Radia, A. and Spaltro, M (2014). The impact of capital requirements on bank lending. *Bank of England Working Paper* 46.

[11] Buch, C., and Prieto, E. (2014). Do Better Capitalized Banks Lend Less? Long-Run Panel Evidence from Germany. *International Finance* 17(1): 1-23.

[12] Calonico, S., Cattaneo, M., and Titiunik, R. (2014a). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica* 82(6): 2295-2326.

[13] Calonico, S., Cattaneo M., and Titiunik, R. (2014b). Robust Data-Driven Inference in the Regression-Discontinuity Design. *Stata Journal* 14(4): 909-946.

[14] Calonico, S., Cattaneo, M., and Titiunik, R. (2015). Optimal data-driven regression discontinuity plots. *Journal of the American Statistical Association* 110(512): 1753–1769.

[15] Calonico, S., Cattaneo, M., Farrell, M., and Titiunik, R. (2016). rdrobust: Software for Regression Discontinuity Designs. *Stata Journal* 17(2): 372-404.

[16] Cattaneo, M., Frandsen, B., and Titiunik, R. (2015). Randomization Inference in the Regression Discontinuity Design: An Application to Party Advantages in the U.S. Senate. *Journal of Causal Inference* 3(1): 1-24.

[17] Cattaneo, M., Titiunik, R., and Vazquez-Bare, G. (2016). Inference in regression discontinuity designs under local randomization. *Stata Journal* 16(2): 331-367.

[18] Cattaneo, M., Idrobo, N. and Titiunik, R. (2017a). A Practical Introduction to Regression Discontinuity Designs: Part I. *Cambridge Elements: Quantitative and Computational Methods for Social Science, Cambridge University Press*, forthcoming.

[19] Cattaneo, M., Idrobo, N. and Titiunik, R. (2017b). A Practical Introduction to Regression Discontinuity Designs: Part II. *Cambridge Elements: Quantitative and Computational Methods for Social Science, Cambridge University Press*, forthcoming.

[20] Cerutti, E., Jihad D., and Giovanni D. (2015). Housing Finance and Real-estate booms: A Cross-Country Perspective. *IMF Staff Discussion Note.*

[21] Cerutti, E., Claessens, S., and Laeven, L. (2017). The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability* 28(C): 203-224.

[22] Cerutti, E., Correa, R., Fiorentino, E., and Segalla, E. (2017). Changes in Prudential Policy Instruments - A New Cross-Country Database. *International Journal of Central Banking, International Journal of Central Banking* 13(2): 477-503.

[23] Claessens, S., Ghosh, S., and Mihet, R. (2013). Macro-prudential policies to mitigate financial system vulnerabilities. *Journal of International Money and Finance* 39(C): 153-185.

[24] Dell'Ariccia, G, Laeven, L., and Marquez, R. (2014). Monetary policy, leverage, and bank risk-taking, *Journal of Economic Theory* 149: 65-99.

[25] Dell'Ariccia, G, Laeven, L., and Suarez, G. (2017). Bank leverage and monetary policy's risk-taking channel: Evidence from the United States. *Journal of Finance* 72(2): 613-654.

[26] Directive 2013/36/EU (CRD) of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directives 2006/48/EC and 2006/49/EC.

[27] European Banking Authority (2014). Guidelines on the criteria to determine the conditions of application of Article 131(3) of Directive 2013/36/EU (CRD) in relation to the assessment of other systemically important institutions (O-SIIs) - EBA/GL/2014/10.

[28] European Systemic Risk Board (2014). The ESRB Handbook on Operationalising Macro-prudential Policy in the Banking Sector.

[29] European Systemic Risk Board (2015). Report on misconduct risk in the banking sector.

[30] Federico, P., Vegh, C., and Vuletin, G. (2012a). Reserve requirement policy over the business cycle. Mimeo.

[31] Furlong, F. and Keeley, M. (1989). Capital Regulation and Bank Risk-taking: a Note. *Journal of Banking and Finance* 13: 883-891.

[32] Galati, G. and Moessner, R. (2013). Macroprudential Policy - A Literature Review. *Journal of Economic Surveys* 27(5): 846-878.

[33] Gelman, A., and Imbens, G. (2014). Why High-order Polynomials Should not be Used in Regression Discontinuity Designs. *NBER Working Papers* 20405, National Bureau of Economic Research, Inc.

[34] Gersbach, H., and Rochet, J. (2012). Capital regulation and credit fluctuations. *CEPR Discussion Papers* 9077, C.E.P.R. Discussion Papers.

[35] Green, D., Leong, T., Kern, H., Gerber, A. and Larimer, C. (2009). Testing the accuracy of regression discontinuity analysis using experimental benchmarks. *Political Analysis* 17: 400–417.

[36] Grembi, V., Nannicini, T. and Troiano, U. (2016). Do Fiscal Rules Matter?. *American Economic Journal: Applied Economics*, American Economic Association. 8(3): 1-30.

[37] Gropp, R., Mosk, T., Ongena, S., and Wix, C. (2016). Bank response to higher capital requirements: Evidence from a quasi-natural experiment. *IWH Discussion Papers* 33/2016, Halle Institute for Economic Research (IWH).

[38] Hahn, J., Todd, P., and Van der Klaauw, W. (2001). Identification and Estimation of Treatment Effects with Regression Discontinuity Design. *Econometrica* 69: 201-209.

[39] Hanson, S., Anil, K., and Jeremy, C. (2011). A macroprudential approach to financial regulation. *Journal of Economic Perspectives* 25: 3-28.

[40] Haldane, A. (2011). Risk off. speech delivered by Andrew G Haldane, Executive Director, Financial Stability and Member of the Financial Policy Committee on 18 August.

[41] Imbens, G. and Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics* 142:.615-635.

[42] Imbens, G. and Kalyanaraman, K. (2012). Optimal Bandwidth Choice for the Regression Discontinuity Estimator. *Review of Economic Studies* 79(3): 933-959.

[43] International Monetary Fund (2011). Macroprudential Policy: An Organizing Framework.

[44] Jiménez, G.,Ongena, S., Peydro, J and Saurina, J. (2014). Hazardous times for monetary policy: What do 23 million loans say about the impact of monetary policy on credit risk-taking? *Econometrica* 82: 463–505.

[45] Jiménez, G., Ongena, S.,Peydro , J. and Saurina, J. (2015). Macroprudential Policy, Countercyclical Bank Capital Buffers and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments. *European Banking Center Discussion Paper* 2012-011.

[46] Lee, D. (2008). Randomized experiments from non-random selection in U.S. House elections. *Journal of Econometrics* 142(2): 675–697.

[47] Lee S. and Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature* 48(2): 281-355.

[48] Lemieux, T. and Milligan, K. (2008). Incentive effects of social assistance: A regression discontinuity approach. *Journal of Econometrics* 142(2): 807-828.

[49] Leonardi, M. and Pica, G. (2013). Who Pays for it? The Heterogeneous Wage Effects of Employment Protection Legislation. *Economic Journal* 123(12): 1236-1278.

[50] Lim, H., Krznar, I., Lipinsky, F., Otani, A. and Xiaoyong, W. (2013). The Macroprudential Framework: Policy Responsiveness and Institutional Arrangements. I*MF Working Paper* 13/166.

[51] Martynova, N. (2015). Effect of bank capital requirements on economic growth: a survey. *DNB Working Paper*.

[52] McCauley, R (2009). Macroprudential policy in emerging markets. Paper presented at the Central Bank of Nigeria‘s 50th Anniversary International Conference on Central banking, financial system stability and growth, Abuja, 4-9 May.

[53] McCrary, J. (2008). Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of Econometrics* 142 (2): 698–714.

[54] Mésonnier, S., and Monks, A. (2015). Did the EBA Capital Exercise Cause a Credit Crunch in the Euro Area? *International Journal of Central Banking* 11(3): 75-117.

[55] Mosk, R., Ongena, T.S., and Wix, C. (2016). Bank response to higher capital requirements: Evidence from a natural experiment. *SAFE Working Paper* 156.

[56] Ongena, S., Popov, A. and Van Horen, N. (2016). The invisible hand of the government: "Moral suasion" during the European sovereign debt crisis. *CEPR Discussion Papers* 11153, C.E.P.R. Discussion Papers.

[57] Noss, J. and Toffano, P. (2014). Estimating the impact of changes in aggregate bank capital requirements during an upswing. *Bank of England Working Paper* 494.

[58] Regulation (EU) No 575/2013 (CRR) of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) 648/2012.

[59] Sanderson, E., and Windmeijer, F. (2015). A weak instrument F-test in linear IV models with multiple endogenous variables. *CeMMAP working papers* 31/15, Centre for Microdata Methods and Practice, Institute for Fiscal Studies.

[60] Shim, I., Bogdanova, B., Shek, J. and Subelyte, A. (2013). Database for policy actions on housing markets. *BIS Quarterly Review* 83-95.

[61] Stein, J. (2014). Incorporating financial stability considerations into a monetary policy framework. Speech at the International Research Forum on Monetary Policy, Washington, D.C., 21 March.

[62] Taylor, J. (2009). Getting off track: How government actions and interventions caused, prolonged, and worsened the financial crisis. Hoover Press: Palo Alto.

[63] Thistlethwaite, D. and Campbell, D. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational Psychology* 51(6): 309-317.

[64] Woodford, M. (2012). Inflation targeting and financial stability. *NBER Working Paper* 17967.

[65] Vadenbussche, J., Vogel, U., and Detragiache E. (2012). Macroprudential Policies and Housing Prices - A New Database and Empirical Evidence for Central, Eastern, and Southeastern Europe. *IMF Working Paper* 12/303.

[66] Van Rixtel, A., and Gasperini, G. (2013). Financial crises and bank funding: recent experience in the euro area. *BIS Working Papers*406, Bank for International Settlements.