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Impact of higher capital buffers on banks' lending and risk-taking: evidence from the euro area experiments

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Abstract

We study the impact of higher bank capital buffers, namely of the Other Systemically Important Institutions (O-SII) buffer, on banks' lending and risk-taking behaviour. The O-SII buffer is a macroprudential policy aiming to increase banks' resilience. However, higher capital requirements associated with the policy may likely constrain lending. While this may be a desired effect of the policy, it could, at least in the short-term, pose costs for economic activity. Moreover, by changing the relative attractiveness of different asset classes, a higher capital requirement could also lead to risk-shifting and therefore promote the build-up (or deleverage) of banks' risk-taking. Since the end of 2015, national authorities, under the EBA framework, started to identify banks as O-SII and impose additional capital buffers. The identification of the O-SII is mainly based on a cutoff rule, ie. banks whose score is above a certain threshold are automatically designated as systemically important. This feature allows studying the effects of higher capital requirements by comparing banks whose score was close to the threshold. Relying on confidential granular supervisory data, between 2014 and 2017, we find that banks identified as O-SII reduced, in the short-term, their credit supply to households and financial sectors and shifted their lending to less risky counterparts within the non-financial corporations. In the medium-term, the impact on credit supply is defused and banks shift their lending to less risky counterparts within the financial and household sectors. Our findings suggest that the discontinuous policy change had limited effects on the overall supply of credit although we find evidence of a reduction in the credit supply at the inception of the macroprudential policy. This result supports the hypothesis that the implementation of the O-SII's framework could have a positive disciplining effect by reducing banks' risk-taking while having only a reduced adverse impact on the real economy through a temporary decrease in credit supply.

Keywords: Macroprudential policy, Systemic risk, Bank capital-based measures, Bank risk-shifting, Credit supply

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

Non-Technical Summary

The entry into force of the new European Union (EU) prudential rules for banks on 1 January 2014 (e.g. Capital Requirements Directive 2013/36/EU (CRD IV), and Regulation (EU) N 575/2013, (CRR)) provided to the macroprudential authorities in the EU a new set of policy instruments to address financial stability risks more effectively. In particular, the CRD IV implemented the Basel Committee on Bank Supervision (BCBS) framework for dealing with domestic systemically important banks (D-SIB) referring to other systemically important institutions (O-SII) which are of systemic importance for the economy of the EU or the relevant Member State. Under the abovementioned framework, national authorities are required to identify banks that are O-SII which could imply, on a consolidated or sub-consolidated or individual basis, as applicable, an O-SII buffer of up to 2 percent of the total risk exposure amount. This macroprudential policy aims to reduce the systemic risks to financial stability due to misaligned incentives and moral hazard based on the perception that some institutions are too big to fail and the role of implicit government guarantees.

Similar to other macroprudential measures that impose higher capital requirements, the O-SII buffer aims to increase banks' resilience to adverse shocks and, at the same time, it may impose some constrains on lending. Moreover, these measures can also lead to risk-shifting and therefore promote the deleveraging of banks. While this may be a desired effect of the policy, it also poses additional costs to the economic activity. The level of these capital buffers is designated based on the capital to risk-weighted assets ratio, therefore banks can meet the capital buffer requirement in two ways. First, banks could decrease their risk-weighted assets by either shifting investments to assets with lower risk-weights or decrease lending altogether. Secondly, banks could issue new equity. In this paper, we focus in the impact of the introduction of the O-SII framework in Euro Area countries (also part of the Single Supervisory Mechanism (SSM)) on banks' lending and risk-taking behaviour.

Since the end of 2015, national authorities started to identify O-SII banks and set additional capital surcharges in terms of Common Equity Tier 1 (CET1) ratio (namely the O-SII buffer). Based on the EU framework, national authorities compute banks with a score equal to or higher than a predetermined threshold, which automatically designates a bank as an O-SII. In a second step, national authorities assess whether further institutions are also systemically relevant in order to be designated as O-SII. Our strategy exploits both the policy change and the discontinuity induced by the O-SII identification process. The key underlying assumption is that there exists a window around the threshold such that the assignment above or below the cutoff is probabilistic and the outcomes depend directly from the score.The EU protocol induces a randomized experiment in the neighbourhood of the threshold allowing to causally identify the effect of higher capital requirements by comparing the change in the outcome of banks just above and below the cutoff.

Relying on granular confidential supervisory data we find evidence that banks identified as O-SII reduced, in the short-term, their credit supply to households and financial sectors and shifted their lending to less risky counterparts within the non-financial corporations sector. In the medium-term, the impact on credit supply is attenuated, and banks continue to shift their lending to less risky counterparts within the financial and household sectors. In terms of policy implications, the results show that regulatory capital buffers have a positive disciplining effect by reducing banks' risk-taking while having only a reduced adverse impact on the real economy through a temporary decrease in credit supply.

1 Introduction

The literature on the effectiveness of macroprudential instruments is still scarce and has so far provided only limited guidance for policy decisions. Part of the explanation is the limited experience with implementing macroprudential policy measures. As a matter of fact, some measures - that have been widely considered as macroprudential - were taken already in the 1930s and 1950s to support the domestic financial system and influence the supply of credit (Haldane (2011)).[1] The suite of monetary, fiscal and prudential policies have been considered sufficient to ensure macroeconomic and financial stability. The recent financial crisis has led to a reconsideration of this consensus. In particular, it has become clear that developments in the financial system are relevant for macroeconomic stability, even when inflation is low and stable, and fiscal positions seem to be sound. However, one of the key challenges is making a holistic assessment of a macroprudential stance (Stein (2014), Galati and Moessner (2013), Woodford (2012) and Taylor (2009)). This requires an understanding of the suitability of an instrument with respect to the objective of containing systemic risk and of the interactions between macroeconomic and macroprudential instruments. Despite many challenges, increasing efforts have been made in recent years to fill these gaps. In 2011, the IMF conducted a survey to take stock of international experiences with financial stability and changes in the macroprudential policy framework (IMF (2011)). The survey was later complemented by Claessens et al. (2013) and the IMF Macroprudential Policy Survey database.[2]

Following recent progress, a strand of literature has attempted to shed light on the link between capital regulation and economic growth. Recent progress on data collection include Shim et al. (2013), who put together an international database on policy actions related to the housing markets. 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 database on legal rather than actual reserve requirements for 15 industrial and 37 developing countries for 1970 until 2011. Cerutti et al. (2017c) built a new database that focuses on changes in the intensity in the usage of several widely used prudential tools, taking into account both macro-prudential and micro-prudential objectives. Budnik and Kleibl (2018) built a new comprehensive data set on policies of a macroprudential nature in the banking sectors of the 28 member states of the European Union (EU) between 1995 and 2014. The focus of most papers has been on the effects of buffer requirements on the cost of banks' capital and credit supply, which in turn could have an impact on the real economy. Along

[1] In addition, central banks in emerging market countries have been regular practitioners of macroprudential policies (McCauley (2009)).

[2] Using this survey, Lim et al. (2013) construct a so-called macroprudential index, while Cerutti et al. (2017a, 2017b, 2017c) provide a valuable perspective on how countries are effectively using prudential instruments throughout business and financial cycles.

this paper causally assesses the effectiveness of higher capital requirements by exploiting the institutional setting used to apply additional capital surcharges to Other Systemically Important Institutions (O-SII) in the Single Supervisory Mechanism (SSM).[3]

Since the beginning of 2015, more than a 110 banks were identified as O-SII and some of them were charged with supplementary requirements concerning the amount of CET1. While the policy implementation differed across countries in calibration methodologies and phase-in arrangements, in most cases the identification of O-SII was done in accordance with the European Banking Authority (EBA) guidelines (EBA (2014)). Under these guidelines, each bank receives a score based on four mandatory indicators which should reflect its systemic importance. Banks with a score above a country-specific threshold are automatically designated as O-SII.[4]

The characteristics of the O-SII framework provides us with an ideal feature to causally assess the impact of higher capital requirements on banks' lending behaviour.[5] By exploiting the discontinuity induced by the EBA selection rule, we can estimate the impact of increased capital surcharges on credit growth and risk-taking of banks close to the threshold. This empirical strategy aims to estimate the effect of regulatory shocks by comparing changes in credit growth and risk-taking of banks just above and below the threshold. Relying on granular supervisory data, we find that banks identified as O-SII shifted their lending behaviour in terms of risk-taking but not in terms of volume. Evidence suggests that banks designated as O-SII reduced, in the short-term, their credit supply to households and financial sectors and shifted their lending to less risky counterparts within the non-financial corporations. In the medium-term, the impact on credit supply is diluted and banks shifted their lending to less risky counterparts within the financial and household sectors. Considering the hypothesis that moral hazard costs lead to excessive risk-taking (Rochet, 1992), this finding suggests that the introduction of the O-SII surcharge 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. 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.

Following the conclusions of Buch and Prieto (2014), our analysis indicates non-significant impact on credit growth for banks close to the threshold in the medium run. Nevertheless, at inception of the imple-

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

[4]The national authorities maintain some discretion when identifying O-SII. In general, this leads to banks below the threshold being identified as O-SII and banks above threshold not being identified as O-SII.

[5]As referred by Gropp et al (2018) banks can increase their capital ratios in two different ways: they either increase their level of equity (the numerator of the capital ratio) or decrease their risk-weighted assets (the denominator of the capital ratio). Our analysis is focused on the denominator of the capital ratio in order to assess banks' lending behaviour.

mentation of the O-SII's framework the tightening of capital requirements had effected the negatively the lending to some counterparties. Peek and Rosengren (1997) find binding risk-based capital requirements associated with the Japanese stock market decline resulted in a decrease in lending by Japanese banks in the United States. Aiyar et al. (2014 and 2016), Gropp et al. (2018) and Fraisse et al. (2017) find that banks constrained with higher capital requirements tend to increase their capital ratios not by raising their level of equity but by reducing their credit supply. Noss and Toffano (2014) suggest that an increase of 15 basis points in aggregate capital ratio requirements of banks operating in the United Kingdom is associated with a median reduction of around 1.4 percent in the level of lending after 16 quarters. De Jonghe et al. (2016) find that higher capital requirements correspond with balance sheet adjustments as well as lower credit supply to corporations. However, the unintended consequences of additional capital buffers on credit supply are minimal. Becker et al. (2014) find strong evidence of the substitution of loans with bonds at times of tight lending standards, depressed aggregate lending and a tight monetary policy. Bridges et al. (2014) show that in the year following an increase in capital requirements, banks, on average, cut loan growth (with a decreasing magnitude) on commercial real estate, other corporates and secured lending to household. Nevertheless, loan growth mostly recovers within three years. In concordance with these results, Martynova (2015) suggests that banks facing higher capital requirements can reduce both credit supply and credit demand by raising lending rates, which may slow down the economic growth. However, better capitalized banks enhance financial stability with reduced risk-taking incentives and increased banks' buffers against losses. Although the theoretical literature indeed suggests that this may be the case, existing empirical evidence does not reach a consensus on the short-term response of credit supply to increased capital requirements. The magnitude and sign of the response often remains highly dependent on institutional factors. Adequate phase-in arrangements, for instance, 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 is generally phased-in over several years, which provides a rationale for the absence of effects on the credit volume.

Our paper contributes to two strands of literature. First of all, it supports empirical literature in which the effect of capital policy regulation is analysed using granular bank-level data. Mésonnier and Monks (2015) exploit a unique monthly data set of Euro Area banks' balance sheets to document the impact of the EBA's capital exercise on banks' lending. They find that banks experiencing a one percent increase in CET1 requirement had an annualized loan growth (over nine months) of 1.2 percent lower than unaffected banks. Gropp et al. (2018) study the impact of higher capital requirements on banks' balance sheets and its transmission to the real economy. Using a matching difference-in-differences strategy that exploits the selection rule of the 2011 EBA capital exercise, the authors show that EBA banks increase their CET1 ratio more than non-EBA banks in response to an increase in capital requirements. Authors also show that banks do not increase their capital ratios by increasing their CET1 capital but by reducing credit supply. In turn, this decrease has significant effects on lending to the corporate sector. This conclusion follows the policy-induced credit crunch concerns of Acharya et al. (2011). However, as referred by Hanson et al. (2011), there are adverse effects if banks decrease lending via deleveraging. Jimenéz et al (2015) find that dynamic loan provisioning can address cyclical features by increasing capital requirements when systemic risks build up. Auer et al. (2016) examine the compositional effects of Switzerland's countercyclical capital buffer (CCyB), a specific targeted macroprudential policy for real estate. Authors find that the introduction of the CCyB led to both an increase in the amount and the cost of lending to corporations, in particular to small firms and commercial real estate. Second, our paper contributes to the literature on the effect of central banks' actions on risk-taking. A recent line of research, for instance, has focused on the 'risk-taking' channel of monetary policy[6] (Adrian and Shin (2008, 2010a and b), Jiménez et al. (2014 and 2017)). The theoretical research on the risk-taking channel has been increasing significantly during the last few years (Yener et al. (2018), Dell'Ariccia et al.(2014 and 2017) and Adrian and Shin (2008, 2010a and b)). Yener et al. (2018) suggest that macroprudential tools have a significant impact on banks' risk-taking. As showed by Borio and Zhu (2012) and Adrian and Shin (2009), in the run up to the crisis, a prolonged low interest rate environment might fuel an asset price boom and lead banks towards taking excessive risks and leverage. Dell'Ariccia et al. (2014) find that the strength of the risk-shifting effect is determined by the level of leverage and that the impact of monetary policy on risk-taking depends on the level of bank capitalisation. Admati et al. (2018) suggest that the shareholders of banks prefer to increase their capital ratios by reducing risk-weighted assets instead of raising new capital.

The remainder of the paper is organized as follows. Section 2 describes the identification process of an O-SII, as established in the EBA guidelines. Section 3 presents the data, while Section 4 explains the identification strategy and lays out the results. Section 5 reviews the validity of our empirical strategy and provides several robustness checks. Section 6 concludes.

2 The O-SII 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-SII.[7] In the first step, the national authorities calculate a score for each banking group at the highest level of consolidation in their jurisdiction. The scoring process,

[6] Considering, that in an environment of persistent low interest rates banks are incentivised to take more risk unto their balance sheets.

[7] Although the EBA guidance is not compulsory, almost all countries in the SSM followed these guidelines.

established in the guidelines, is based on four 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 a predetermined country-specific threshold. The standard value of the threshold is set at 350 basis points. National authorities consider the idiosyncrasies of the banking sector and the resulting statistical distribution of scores, which can be reflected in a higher threshold (maximum 425 basis points) or lower threshold (minimum 275 basis points).[8]

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

Criterion	Indicators
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

The second step of the procedure entails national supervisory overlay. In order to apply a supervisory overlay, the relevant authorities may select additional indicators considered adequate in capturing systemic risk in their domestic sector or in the economy of the country.[9] This secondary supervisory judgment is typically applied to identify as O-SII banks banks which were not identified based on automatic score. Only in few cases this supervisory judgment was applied to reverse an O-SII identification for a bank above the threshold, due to national idiosyncrasies, a small and concentrated banking system or ongoing liquidation (Table 2).

From the 1st of January 2016, national authorities started to implement stricter capital requirements, typically in the form of CET1 capital buffers.[10] As the EBA guidelines do not provide any guidance on how

[8] In 2015, most of the countries set the threshold at the standard level (350 basis points), while two countries lowered it to 275 basis points. Luxembourg decided to set the threshold for automatic identification at 325 basis points and Slovakia at 425 basis points.

[9] 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.

[10] In few countries the O-SII surcharge was complemented with the introduction of the systemic risk buffer.

the O-SII buffer should be calibrated, EU countries have used various methods, and sometimes additional indicators, for the valuation of O-SII buffers.[11] However, EU legislation provides some constraints: an upper limit of 2 per cent, and for subsidiaries of Global Systemically Important Institutions (G-SII) or O-SII the buffer cannot exceed the higher of 1 percent and the G-SII or O-SII buffer applicable at the consolidated level of the banking group.

Similar to the calibration of the buffer, the timing and pace 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 seven countries decided to defer the implementation of a positive O-SII capital surcharge beyond 2016.[12] In addition, different multi-year linear phase-in periods have been adopted. Estonia, Finland, Lithuania and Slovenia are the only countries that required a fully loaded implementation already from the first year.

Table 2: O-SII implementation in SSM / Euro Area countries (reference date end-2015)

	Number of banks		Average Score		Sup.	Date of Decision	O-SII Buffer	
	(1) O-SII	Not O-SII	O-SII	Not O-SII	Judg.		Jan-16	Dec-20
Austria	7 (6)	137	968	37		29/4/2016	[0, 0]	[0, 2]
Belgium	7 (8)	25	1189	87	Y	30/10/2015	[0, 0.5]	[0, 1.5]
Cyprus	6 (6)	6	1581	146		30/12/2015	[0, 0]	[0, 1]
Germany	16 (15)	158	457	12	Y	30/12/2015	[0, 0]	[0, 2]
Estonia	2 (2)	7	2562	292	Y	02/12/2015	Only Identification	
Spain	6 (6)	51	1312	44		26/11/2015	[0, 0.25]	[0, 1]
Finland	4 (3)	242	2778	24		06/07/2015	[0, 2]	[0, 2]
France	6 (6)	145	1424	61	Y	17/11/2015	[0, 0.375]	[0, 1.5]
Greece	4 (4)	4	2483	32		21/12/2015	[0, 0]	[0, 0.5]
Ireland	2 (2)	23	1932	43		16/11/2015	[0, 0]	[0, 1]
Italy	3 (3)	126	2194	52		30/12/2015	[0, 0]	[0, 0]
Lithuania	4 (4)	3	2090	97		15/12/2015	[0, 0]	[0, 2]
Luxembourg	6 (6)	62	614	58	Y	30/11/2015	[0, 0.25]	[0, 1]
Latvia	6 (6)	9	1171	162		16/12/2015	Only Identification	
Malta	3 (3)	16	1194	76	Y	07/12/2015	[0, 0.5]	[0, 2]
Netherlands	5 (5)	28	1767	37	Y	11/12/2015	[0, 0.5]	[0, 2]
Portugal	7 (6)	119	1258	50		23/11/2015	[0, 0]	[0, 1]
Slovenia	8 (4)	9	1037	168		22/12/2015	[0, 0]	[0, 1]
Slovakia	5 (5)	6	1141	157		04/06/2015	[0, 1]	[0, 2]

Notes: Reference date end first year of implementation according to the CRD IV. (1) Number of banks identified as O-SII and in brackets the number of banks available in the database

[11] 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.

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

3 Data

In order to assess the effect of implementation of the O-SII framework on credit supply and risk-taking the analysis relies on granular confidential supervisory data, which is reported quarterly for SSM banks between the last quarter of 2014 up to the last quarter of 2017. The data includes information on volumes of exposures, risk-weighted assets, impairments and expected losses, as well as indicators of capital, such as the Common Equity Tier 1 (CET1) ratio. In addition, we rely on the information on the annual assessment of O-SII, which includes the level of the required capital buffer, and the date of notification, publication and implementation of the policy measure. Complementing confidential supervisory data with the information provided by national authorities, we were able to estimate the overall score of almost 1,300 banks from 19 Euro Area countries and their distance from the threshold for the automatic identification.[13] Out of almost 1,300 entities, more than 110 were identified as O-SII at least once during the period considered [14], the vast majority of which qualifies as Significant Institutions (SI) or subsidiaries domiciled in other Member States.

Table 3: Descriptive statistics

	Not O-SII		Bank above the threshold	
	Pre-notification	Post-notification	Pre-notification	Post-notification
Δ *Log Credit (quarterly)*				
Households	0.008	0.007	-0.001	0.006
	(0.335)	(0.311)	(0.222)	(0.215)
Non-financial corporations	0.003	-0.001	0.0004	-0.001
	(0.422)	(0.415)	(0.142)	(0.139)
Non-financial private sector	0.007	0.005	0.002	-0.001
	(0.267)	(0.236)	(0.092)	(0.081)
Financial sector	-0.002	0.008	-0.021	-0.025
	(0.577)	(0.566)	(0.299)	(0.274)
Δ *Risk-Weight (quarterly)*				
Households	-0.045	-0.002	-0.002	-0.003
	(2.721)	(0.031)	(0.063)	(0.101)
Non-financial corporations	-0.003	0.0004	-0.0018	-0.001
	(0.066)	(0.102)	(0.045)	(0.051)
Non-financial private sector	-0.004	-0.001	-0.003	-0.002
	(0.158)	(0.056)	(0.025)	(0.027)
Financial sector	0.0001	-0.002	-0.004	0.0003
	(0.079)	(0.067)	(0.052)	(0.05)

Notes: Data between 2014:Q4 to 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 credit growth rate is the change in the log of a banks' credit volume. The quarterly changes are in percentage points.

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

[14] The group of O-SII includes 7 Less Significant Institutions (LSIs) and one institution (an export corporation in Slovenia) which is not a bank.

In Table 3, it is presented 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.[15]

In order to identify how banks adjust their balance sheets in response to higher capital buffer requirements, i.e. to estimate the causal effect of a bank being identified as an O-SII on lending and risk-taking behaviour, different indicators using the exposure at default (EAD) as a measure of total exposures are considered.[16] To quantify changes in levels of banks' lending, the credit growth rate in the natural logarithm of a banks' total exposures is calculated.[17] To assess banks' risk-taking, the change in the average risk-weights or risk-weighted asset densities is considered.[18] The average risk-weights, defined as the ratio of risk-weighted assets to total exposures, is widely used to measure the average risk of exposures taken by a bank. For standard approach (STA) exposures the risk-weights are defined according external ratings or level of collateralisation, as detailed in the Regulation (EU) No 575/2013 ('CRR'). For internal ratings based approach (IRB) exposures the risk-weights are calculated according to Articles 153 and 154 of the CRR.[19]

[15] Additional descriptive statistics are reported in Table A1 in the Appendix.

[16] 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, the longer-term refinancing operations (LTRO) program of the European Central Bank (ECB) (Van Rixtel and Gasperini (2013)). The EAD might be considered as a measure of size, which includes both on-balance-sheet and off-balance-sheet contingent exposures and commitments (converted into equivalent on-balance-sheet amounts through the application of credit conversion factors).

[17] We also compute the net change in credit computed as the quarterly variation in exposures plus redemptions, i.e.: $Credit\ Flow_t = (Exposures\ at\ Default_t - Exposures\ at\ Default_{t-1}) + Redemptions_t$. The results do not change substantially.

[18] This indicator is also 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).

[19] Risk-weights depend on the probability of default (PD) and the type of the exposure. If $0 < PD < 1$ risk-weights are computed as:

1. for exposures to corporate, institutions and central governments and central banks
   $RW = \left(LGD \cdot N\left(\frac{1}{\sqrt{1-R}} \cdot G(PD) + \sqrt{\frac{R}{1-R}} \cdot G(0.999)\right) - LGD \cdot PD\right) \cdot \frac{1+(M-2.5)\cdot b}{1-1.5\cdot b} \cdot 12.5 \cdot 1.06$
   where PD is the probability of default of the counterpart; LGD is the loss given default; $N(x)$ is the cumulative distribution function for a standard normal random variable (i.e. the probability that a normal random variable with mean zero and variance of one is less than or equal to x); $G(z)$ denotes the inverse cumulative distribution function for a standard normal random variable (i.e. the value x such that $N(x) = z$); R denotes the coefficient of correlation, is defined as $R = 0.12 \cdot \frac{1-e^{-50\cdot PD}}{1-e^{-50}} + 0.24 \cdot \left(1 - \frac{1-e^{-50\cdot PD}}{1-e^{-50}}\right)$ and b the maturity adjustment factor, which is defined as $b = (0.11852 - 0.05478 \cdot \ln(PD))^2$. For non-financial corporations with total annual sales less than Eur 50 million, $R = 0.12 \cdot \frac{1-e^{-50\cdot PD}}{1-e^{-50}} + 0.24 \cdot \left(1 - \frac{1-e^{-50\cdot PD}}{1-e^{-50}}\right) - 0.04 \cdot \left(1 - \frac{\min\{\max\{5,S\},50\}-5}{45}\right)$, where S denotes the total annual sales in millions of Euros with $5 \leq S \leq 50$.
2. for exposures to retail $RW = \left(LGD \cdot N\left(\frac{1}{\sqrt{1-R}} \cdot G(PD) + \sqrt{\frac{R}{1-R}} \cdot G(0.999)\right) - LGD \cdot PD\right) \cdot 12.5 \cdot 1.06$ where for mortgages $R = 0.15$ and qualifying revolving retail exposures $R = 0.04$. Elsewhere $R = 0.03 \cdot \frac{1-e^{-35\cdot PD}}{1-e^{-35}} + 0.16 \cdot \left(1 - \frac{1-e^{-35\cdot PD}}{1-e^{-35}}\right)$.
3. if $PD = 1$ risk-weights are computed for all type of exposures as $RW = \max\{0, 12.5 \cdot (LGD - ELbe)\}$, where the expected loss best estimate ($ELbe$) shall be the institution's best estimate of expected loss for the defaulted exposure in accordance with Article 181(1)(h) of the CRR.

4 The empirical model

4.1 Identification strategy

Determining the effect of the identification of a bank as systemically important and introducing higher capital requirements on banks' credit supply and risk-taking behaviour is challenging. Especially since the introduction of capital surcharges may be correlated with credit supply and risk-taking. Capital buffer requirements, for instance, reflect the actual and expected capitalization, as well as the size and profitability of banks. Therefore, our estimate is likely to suffer from a reverse causality problem, for example riskier banks may be more probably subject to tighter capital restrictions.[20] To address these challenges, we rely on a peculiarity of the institutional framework discussed above, namely the fact that the identification of the O-SII and the application of the related capital buffer are determined by a predefined threshold. As covered in the previous section, EBA's guidelines on the identification of O-SII establish a scoring process 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 the national banking system. And most crucially, institutions with a score equal to or higher than a certain threshold are automatically identified as O-SII.

Although the automatic calculation has been complemented with supervisory judgment, the O-SII framework provides a natural setting for a regression discontinuity design.[21] This strategy exploits both the policy change and the discontinuity induced by the O-SII identification process. The key underlying assumption is that there exists a window around the threshold such that the assignment above or below the cutoff is probabilistic and the outcomes depend directly from the score.[22] The EBA assessment protocol induces a randomized experiment in the neighbourhood of the threshold allowing to causally identify the effect of higher capital requirements by comparing the change in the outcome of banks just above and below the cutoff. In order to understand our identification strategy, consider a setting where we have a sample of N banks, indexed by $i = 1,...,N$, which are followed for T time periods, indexed by $t = 1,...,T$. Let $I_{i,t}$ be the (binary) treatment status for bank i at time t. In our context, if $I_{it} = 1$ the bank is identified as O-SII and

[20] A difference-in-differences approach is unlikely to solve these issues because several observed and unobserved bank characteristics affect both the adoption of the policy and the trends of the potential outcomes. This design would be invalidated if banks of different sizes followed different trends before the adoption of the measure.

[21] These designs were first introduced in the evaluation literature by Thistlethwaite and Campbell (1960). Leonardi and Pica (2013) apply a differences-in-discontinuities 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 regression discontinuity designs for evaluating causal effects of interventions, where assignment to a treatment is determined at least partly by the value of an observed covariates lying on either side of a fixed threshold.

[22] 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 other covariates in a window around the cutoff, and the potential outcomes are allowed to depend directly of the score.

$I_{i,t} = 0$ otherwise. Formally, the treatment assignment is given by:

$$I_{i,t} = \begin{cases} 1 & \text{if } S_{i,t} \geqslant THOLD_{c(i),t} \text{ and } t \geqslant \tau_{c(i),t} \\ 0 & \text{otherwise.} \end{cases}$$

where $S_{i,t}$ is bank i's score used for the annual review. $THOLD_{c(i),t}$ is the threshold based on which a bank is identified as an O-SII. The threshold $THOLD_{c(i),t}$ can vary across countries where $c(i)$ is the country where bank i is domiciled. Based on the EU directive, national authorities shall review annually the identification of O-SII, though the precise timing and pace is discretionary to each national authority. Therefore, $\tau_{c(i),t}$ is the year in which the review is effective and it could be different across countries.[23] In order to simplify, we refer to $THOLD_{c(i),t}$ as $THOLD$ and to $\tau_{c(i),t}$ as τ.

Since we are interested in studying the effect of the identification $(I_{i,t})$ on banks' behaviour $(Y_{i,t})$, let us denote $Y_{it}(0)$ and $Y_{i,t}(1)$ the potential outcomes of the variables of interest. Then, for each bank i in the sample, the observed outcome is given by:

$$Y_{i,t} = \begin{cases} Y_{i,t}(0) & \text{if } I_{i,t} = 0 \\ Y_{i,t}(1) & \text{otherwise.} \end{cases}$$

The start of the treatment corresponds to the date when the national authorities notified their decision to the ECB.[24] After the notification is issued (i.e. for $t \geqslant \tau$), the treatment status $I_{i,t}$ changes, where banks with a score above a predetermined country-specific threshold are qualified as O-SII and may be charged with an additional capital requirement. 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 already started adjusting their balance sheets as soon as they were notified of their classification as an O-SII. Therefore it is assumed the adjustment period to have started just after the notifications have been issued by the national authorities.

In order to estimate the average treatment effect on the treated (ATT) close to the threshold at inception, we exploit the cross-sectional nature of the database. If the identification is sharp, the point estimate can

[23] Usually $\tau(t)$ does not coincide with the time when the policy decision is implemented, yet for simplicity it is used the same nomenclature for the date of effectiveness and the date of reference of the score.

[24] Article 5(1) of the SSM Regulation requires national competent or designated authorities to notify their intention to the ECB, in ten working days prior to taking the decision, of applying new requirements for capital buffers, including O-SII buffers, where the ECB may object, stating its reasons, within five working days. According to Article 5(2) of the SSM Regulation, the ECB may, if deemed necessary, apply higher requirements for capital buffers, including O-SII buffers, than the ones applied by the national authority.

be obtained estimating the following regression model in an interval around the threshold:

$$Y_{i,t} = \beta_0 + \beta_1 S^*_{i,t} + \beta_2 I_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t}$$

where $I_{i,t}$ is the dummy for banks identified as O-SII and $S^*_{i,t}$ is the distance from threshold (i.e. $S^*_{i,t} := S_{i,\tau_{c(i)}} - THOLD_{c(i),\tau_{c(i)}}$). $X_{i,t}$ is the vector of controls that includes the lagged value of CET1 minus the associated binding capital requirement (ie the distance from the current and required CET1 ratio), the risk-weights density, the return-on-assets (ROA) and the current and future level of the O-SII requirement. Alternatively, a more flexible functional form relative to the distance from the threshold ($S^*_{i,t}$) is also implemented (see Lee and Lemieux, 2010 and Gelman and Imbens, 2014):

$$Y_{i,t} = \beta_0 + \beta_1 f^k(S^*_{i,t}) + \beta_2 I_{i,t} + \beta_3 X_{i,t} + \varepsilon_{i,t}$$

where $f^k\left(S^*_{i,t}\right)$ is a polynomial of order k in $S^*_{i,t}$. The parameter of interest is β_3 which measures the average difference in the relevant economic outcome (namely credit supply and risk-taking) between banks identified and not identified as O-SII.

When focusing on the medium run effect of the macroprudential policy, a longitudinal dataset is used where we control for time fixed effect (u_t) and bank fixed effect (η_c). The inclusion of bank and time fixed effects increases efficiency of the estimate (Calonico et al., 2018, Petterddon-Lidbon, 2008). Adding these fixed effects reflect the rich nature of our panel data, which allows controlling for changes in credit demand (Borio and Gambacorta, 2017).

In the identification process of the O-SII, national authorities consider some banks to be systemically relevant even if their score is below the $THOLD$. Consequently, expert supervisory judgment is applied by the national authority.[25] This implies that the probability of being identified as O-SII changes discontinuously (see Figure 3) at the threshold, leading to the application of a fuzzy regression discontinuity model:

$$\lim_{\varepsilon \to 0^+} \Pr\left(I_{i,t} = 1 \mid S_{i,t} = THOLD + \varepsilon,\ t \geqslant \tau\right) > \lim_{\varepsilon \to 0^-} \Pr\left(I_{i,t} = 0 \mid S_{i,\tau(t)} = THOLD + \varepsilon,\ t \geqslant \tau\right)$$

In this setup, it is possible to 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 $Y^+ = \lim_{\varepsilon \to 0^+} E\left[Y_{i,t} \middle| \ S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$ and $Y^- = \lim_{\varepsilon \to 0^-} E\left[Y_{i,t} \middle| \ S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. The analogous expressions for the treatment status are $I^+ = \lim_{\varepsilon \to 0^+} E\left[I_{i,t} | S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$ and

[25] The identification process of the O-SII is partly determined by factors other than the banks' score, because of national supervisory overlay. If the O-SII assessment were based solely on the banks' individual scores, the OLS estimation for banks with a score in the interval $[S_c - h; S_c + h]$ would be sufficient to identify the effect of interest.

$I^- = \lim_{\varepsilon \to 0^-} E\left[I_{i,t} | S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. In the standard regression discontinuity design setting, the treatment effect is given by:

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

Assuming that potential outcomes are continuous in S at the threshold and observations just above and just below S_c are locally randomized following a parallel trend in the absence of the policy, the ratio π_{FRD} identifies the local average treatment effect (LATE) of a bank being designated as O-SII on the outcome of interest.

4.2 Validation of the identification strategy

The key assumption for casually identifying the effect of the introduction of the O-SII framework is that banks do not actively try to change or manipulate their scores and thus their identification as an O-SII. Since the score of banks depends on each banks' characteristics, on the whole national banking system, as well as on the expert judgment of the national authority, it is unlikely that each bank could "manipulate" its probability of being identified as an O-SII. For example, banks can aim to reduce total assets via deleveraging, although the overall sub-scores (Table 1) will also depend on the behaviour of other banks. In order to validate this assumption, different tests were performed. First, the distribution of the scores around the threshold was analyzed to check if the number of observations below the cutoff is considerably different from the number of observations above it. To perform this test, we follow the procedure of McCrary (2008) where the continuity at the cutoff of the score density is assessed. Figure A1 plots the density of the normalized scores, considering the overall yearly reviews (end-2015, end-2016 and end-2017), and does not reveal any discontinuity in the density at the threshold, which is reassuring the absence of manipulative sorting. In addition, we follow the test proposed by Cattaneo, Jansson and Ma (2015a), where a local polynomial density estimator is used and does not require binning the data (see Figure A2). This test also reassures the absence of manipulative sorting.

Another important falsification test involves examining whether O-SII banks near the cutoff are similar to other banks. The intuition is straightforward, if banks lack of the ability to manipulate the value of the score received, banks just above and below the cutoff should be similar in all those characteristics that could not have been affected by the treatment. In particular, predetermined covariates (e.g. CET1) should be similar across treated and untreated banks. Table A2 shows that for both treated and untreated banks close to the threshold the hypothesis of continuous covariates holds. Moreover, the control variables used in the regressions were tested in order to validate that they are not affected by the implementation of the O-SII framework. To this purpose, we test for variability in the covariates close to the threshold. Figure A3 shows non-significant jumps. These results are encouraging as they provide evidence of the absence of non-random sorting by banks close to the threshold, therefore allowing for a randomized experiment.

5 Results

5.1 Evidence on short-term effects

Estimating the effect of higher capital buffers on a banks' lending behaviour has a number of challenges. First, there is the exogenous variation in capital requirements, which is unobservable and stagnant. Usually when capital buffers change, the adjustment will be for the entire banking system simultaneously, making it practically impossible to identify any casual effects. Secondly, there are cases where supervisors impose bank-specific requirements, which are related to bank characteristics and thus not exogenous with respect to banks' balance sheet. Thirdly, in order to assess the effects of capital requirements on bank lending, it is important to disentangle credit supply from credit demand.

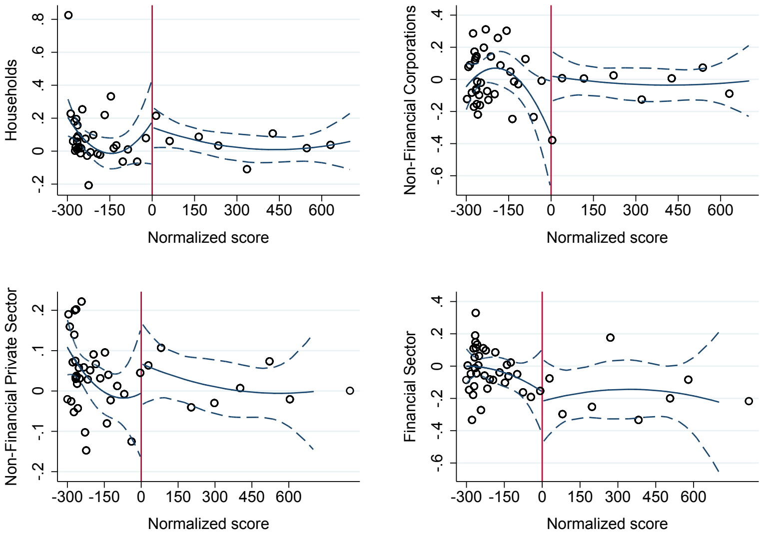
These challenges can be overcome by exploiting the O-SII framework as prescribed by the European regulation (CRD) for the banking industry. The institutional feature of the O-SII framework is particularly well-suited for estimating the casual effect of a bank being identified as an O-SII and the respective introduction of the O-SII capital surcharges. Since the O-SII framework 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 O-SII surcharge. Along these lines, we analyze the extent to which the implementation of the O-SII framework affects the banks' lending behaviour, in particular the changes in the outstanding loan volumes and risk-taking, immediately after the first identification performed by the national authorities. In our specification, in order to select the optimal bandwidth around the threshold, the methods of Calonico, Cattaneo and Titiunik (2014) and Calonico et al. (2018) were used. Also, with the purpose of alleviating the concern that our results are driven by our specification, different specifications and order polynomials for the selection of the bandwidths were considered.

Figures 1 and 2 show the change on credit supply and risk-taking of banks around the threshold, at the end of 2015. For each outcome variable, a scatter plot with its value against the normalized scores is presented ($S^*_{i,t}$),[26] for banks in the neighbourhood of the threshold. Our graphical analysis does not capture the fuzziness of the O-SII identification process and does not allow us to account for time and country fixed effects. However, it gives us a first representation of a potential adjustment in the outcome variables at the

[26] In order to have a comparable measure across countries, we consider the distance of each banks score to the threshold used by the relevant national authority.

cutoff for banks identified as an O-SII. A visual inspection of Figure 1 does not reveal a clear discontinuity in banks' credit supply, suggesting that the effect of identification on the volume of lending may be negligible (e.g. non-financial corporation). Yet, an adjustment can noticed when looking at our measures of risk-taking, especially for households and non-financial private sector - see Figure 2.

Figure 1: Change in credit growth of banks close to the threshold (end-2015)



Notes : The vertical axis displays the outcome variable. The horizontal axis measures the score distance from the threshold. The central line plots fitted values of the regression of the dependent variable on a second-order polynomial in score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

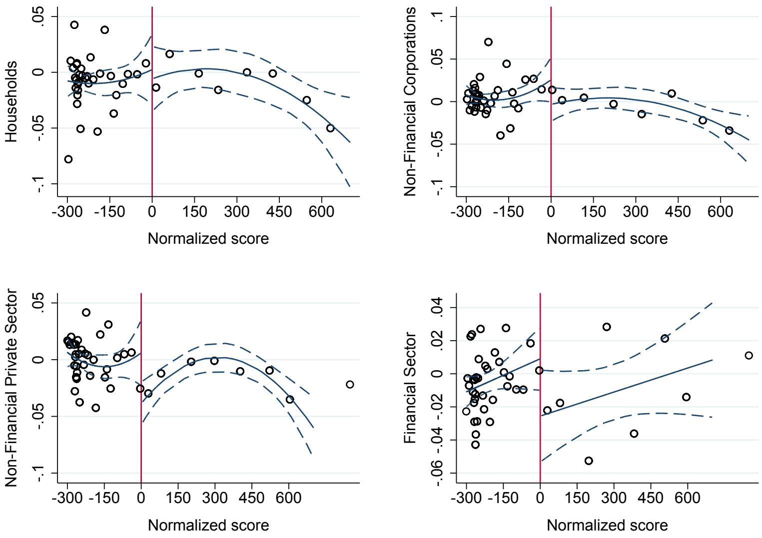
Figure 3 shows the relationship between the score of a bank and an identification of a bank as an O-SII, at the end of 2015. The probability of a bank being designated as O-SII increases significantly and discontinuously if a bank receives a score above the threshold. As mentioned, several institutions below the cutoff are, nevertheless, designated as O-SII because of supervisory judgment.[27] Figure 3 confirms the use of a fuzzy design as appropriate for the setting at hand[28].

The estimates from our specification, to assess the impact of the O-SII framework in banks of the Euro Area (SSM countries) at the end of 2015, are reported in Tables 4 and 5, which present, respectively, the results for credit growth and risk-taking. The dependent variable in Table 4 is the yearly credit growth rate as a change in the log of a banks' credit volume. The dependent variable in Table 5 is the yearly change in the average risk-weights or risk-weighted assets density. Our outcome variables are presented in four exposure classes, namely households, non-financial corporations, non-financial private sector and financial

[27] Nine countries (Belgium, Estonia, France, Germany, Ireland, Luxembourg, Malta, the Netherlands and Spain) complemented the automatic calculation for the identification of the O-SII with supervisory judgment.

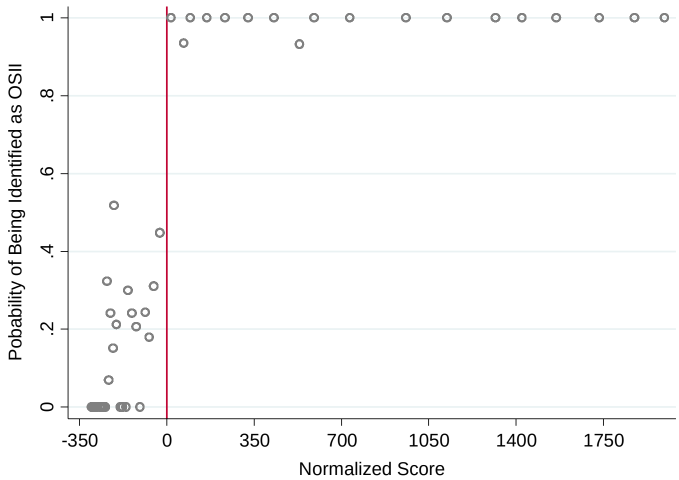
[28] Hahn et al. (2001) shows that a fuzzy regression discontinuity approach is closely related to an instrumental variable setting. For the purpose of identification, it is thus important to document a strong first-stage relationship between the running variable and the conditional probability of assignment to the treatment group.

Figure 2: Risk-weights distribution of banks close to the threshold (end-2015)



Notes : The vertical axis displays the outcome variable. The horizontal axis measures the score distance from the threshold. The central line plots fitted values of the regression of the dependent variable on a first- or second-order polynomial in score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 3: Probability of being identified as OSII as a function of the score



Notes : The figure illustrates the first-stage relationship between normalized score and O-SII identification. The vertical axis displays the proportion of banks that are identified as O-SII. The horizontal axis measures the score distance to the threshold.

sector, to identify the effect of the additional regulatory surcharge on each sector of the economy. Each variable is trimmed to reduce the influence of extreme values in the precision of the estimates. In each table, the coefficient on the interaction between the O-SII dummy and the post-notification dummy, along with the corresponding p-values, are presented.

Focusing on the last quarter of 2015, i.e. the first year when almost all Euro Area countries made their first assessment of O-SII, we find a significant effect in banks identified as O-SII on credit supply to households and financial sectors (Table 4). Our estimates suggest that banks identified as O-SII do not differ in terms of risk-taking from other banks, with exception of banks just above the threshold where a reduction in the risk-weight density for the non-financial corporations is observed (Table 5). These results are robust to the choice of the bandwidth and to the order of the polynomial (see Tables A3 and A4 in the Appendix).

The timing for the implementation of the policy was heterogeneous and some countries postponed the activation of a non-zero capital buffer beyond the end of our sampling period. The phase-in of the buffer requirement was delayed exactly in order to allow banks to smoothly adjust their balance sheets, therefore reducing the short-term effects of the O-SII buffer tightening. Given this setting, there is a need to control for country and bank characteristics, for this reason the following controls were considered: the yearly lagged credit-to-GDP gap in each country, the yearly lagged distance from the actual and the required CET1 ratio[29] for each bank at the end of 2014, and the lagged banks' risk-weight density at the end of 2014. Moreover, the levels of the O-SII buffer at the end of 2015 and the end of 2020 are controlled. Tables 4 and 5 show the results and there is not a significantly change compared to the initial specification.[30] Also, we rule out the possibility that our results may be driven by the (aggregate) credit cycle. For this purpose, the credit-to-GDP gap, defined as the difference of credit-to-GDP from its long-run trend in percentage points, is included in our baseline regression. Adding an indicator of the financial cycle allows us to better control for observed and unobserved time-varying heterogeneity at the country level.

These results reflect also the fact that the implementation of the buffer requirements for the O-SII was phased-in over several years and only a subset of institutions needed to meet a non-zero capital surcharge by the end of our sampling period. The timing and pace for the activation of the measure may have attenuated its adverse impact on the real economy and provided a rationale for the limited short-term effects on the volume of lending.

5.2 Evidence on the medium-term effects

The use of cross-sectional bank balance sheet data is appropriate for investigating short-term effects on banks' behaviour in response to the implementation of the O-SII framework, however it is not suitable for identifying the medium-term effects on banks' risk-taking behaviour and credit supply. In particular, by using a purely cross-sectional approach, it is not possible to disentangle credit supply from credit demand.

[29]The regulatory CET1 ratio is computed as the one resulting from Pillar 1 and Pillar 2 requirements, capital conservation buffer, countercyclical capital buffer, global systemically important institutions and other systemically important institutions buffers and systemic risk buffer.

[30]We also estimate the model by restricting the countries where the designated O-SII buffer was strictly positive by the second quarter of 2016.

Table 4: Credit Growth: Average effect of O-SII identification by economic sector (end-2015)

	Households	Non-financial corporations	Non-financial private sector	Financial sector
ΔLog Credit				
MSE-optimal bandwith	-0.17**	0.758	-0.003	-1.212**
(p-value)	0.023	0.590	0.931	0.035
Bandwith	[-62, 605]	[-183, 275]	[-126, 687]	[-116, 856]
Observations	41	65	56	53
Order of polynomial	2	2	2	2
MSE-optimal bandwith	-0.178**	0.646	-0.002	-1.189
(p-value)	0.016	0.947	0.665	0.170
Bandwith	[-50, 491]	[-149, 223]	[-103, 558]	[-94, 695]
Observations	34	53	48	50
Order of polynomial	2	2	2	2
Controls	None	None	None	None
	Households	Non-financial corporations	Non-financial private sector	Financial sector
ΔLog Credit				
MSE-optimal bandwith	-0.149***	0.635	-0.055	-1.406***
(p-value)	0.001	0.391	0.245	0.000
Bandwith	[-67, 315]	[-172, 342]	[-119, 409]	[-50, 62]
Observations	27	63	43	14
Order of polynomial	2	2	2	1
MSE-optimal bandwith	-0.159***	0.612	-0.121	-1.685***
(p-value)	0.000	0.560	0.090	0.000
Bandwith	[-54, 256]	[-140, 278]	[-97, 332]	[-42, 52]
Observations	25	53	36	10
Order of polynomial	2	2	2	1
Controls	Country and bank specific	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the effect of O-SII identification on credit growth. The dependent variable is the yearly growth rate as a change in the log of a banks' credit volume. We perform local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at the country level. The lower panel of results includes credit-to-GDP gap for each country, distance from the current and required CET1 ratio and the banks' risk-weight density of each bank. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively. The controls includes the credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank at the end of 2014, the banks' risk-weight at the end of 2014, the O-SII buffer level at the end of 2014, at the end of 2015 and the end of 2019.

Thus, to study the medium-term effects of the identification of O-SII on banks' lending and risk-taking, we follow the study of Gambacorta and Mistrulli (2004) by using longitudinal data.

Looking at the first three yearly assessments of O-SII, it is possible to assess the banks' behaviour while being able to control for time varying capital requirements and observable banks' characteristics. Starting from a graphical representation, it is possible to observe changes in the credit supply and in the risk-taking

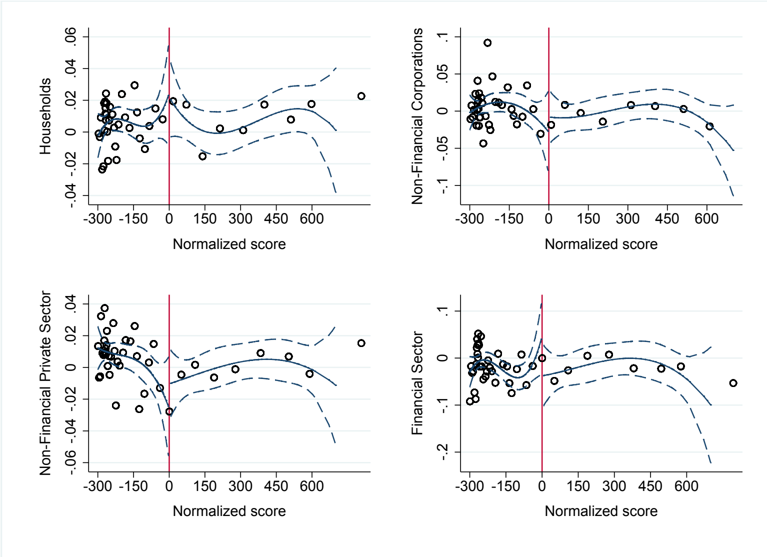
Table 5: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector (end-2015)

	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ*Risk-weights*				
MSE-optimal bandwith	-0.012	-0.019	0.008	-0.03
(p-value)	0.383	0.605	0.595	0.652
Bandwidth	[-148, 489]	[-151, 834]	[-96, 569]	[-114, 557]
Observations	46	69	46	46
Order of polynomial	2	2	2	2
MSE-optimal bandwith	-0.006	-0.029	-0.006	-0.074
(p-value)	0.260	0.488	0.286	0.935
Bandwith	[-120, 397]	[-122, 678]	[-78, 462]	[-93, 453]
Observations	35	53	33	37
Order of polynomial	2	2	2	2
Controls	None	None	None	None
	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ*Risk-weights*				
MSE-optimal bandwith	-0.025	-0.067***	0.003	0.023
(p-value)	0.408	0.000	0.739	0.119
Bandwith	[-159, 507]	[-89, 181]	[-66, 256]	[-63, 335]
Observations	59	23	25	28
Order of polynomial	2	2	2	2
MSE-optimal bandwith	-0.032	-0.053***	0.013	0.025
(p-value)	0.290	0.000	0.150	0.099
Bandwidth	[-130, 412]	[-72, 147]	[-53, 208]	[-52, 273]
Observations	46	20	20	26
Order of polynomial	2	2	2	2
Controls	Country and bank specific	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the effect of O-SII identification on risk-taking. The dependent variable is the yearly change in the average risk-weights. We perform local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at the country level. The lower panel of results includes credit-to-GDP gap for each country, distance from the current and required CET1 ratio and the banks' risk-weight density of each bank. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively. The controls includes the credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank at the end of 2014, the banks' risk-weight at the end of 2014, the O-SII buffer level at the end of 2014, at the end of 2015 and the end of 2019.

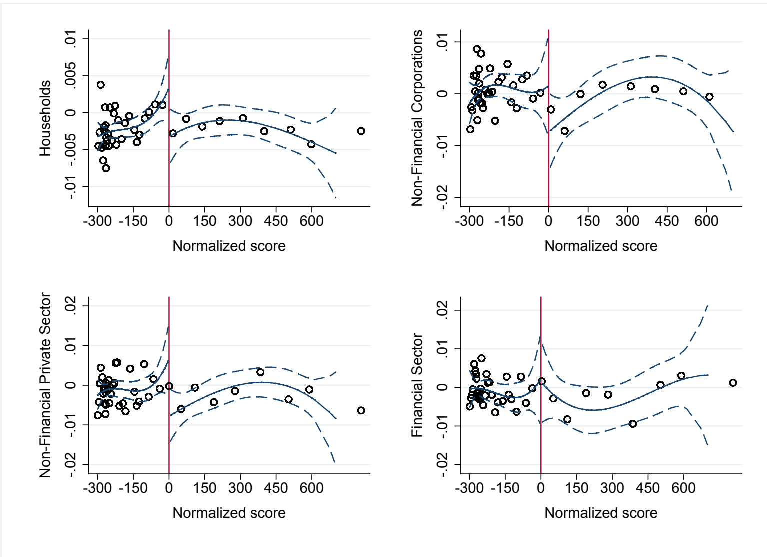
of banks identified as O-SII. Figures 4 and 5 show the unconditional quarterly change of credit and the quarterly change of risk-weights density of banks around the threshold, from the end of 2015 to the end of 2017. For each outcome variable, a scatter plot with its value against the normalized scores is presented for banks in the neighbourhood of the threshold. The visual inspection does not reveal a clear discontinuity in banks' credit supply, suggesting that the effect of banks being identified as O-SII on the volume of lending may be negligible (e.g. non-financial corporation). Yet, it is possible to detect an adjustment when looking at our measures of risk-taking, in particular in the households sector.

Figure 4: Change in credit growth close to the threshold (end-2015 - end-2017)



Notes : The vertical axis displays the outcome value. The horizontal axis measures the score distance from the threshold. The central line plots fitted values of the regression of the dependent variable on a third-order polynomial in score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 5: Change in credit growth close to the threshold (end-2015 - end-2017)



Notes : The vertical axis displays the outcome value. The horizontal axis measures the score distance from the threshold. The central line plots fitted values of the regression of the dependent variable on a third-order polynomial in score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

The data used is of quarterly frequency, from the end of 2015 to the end of 2017, for banking institutions in 19 Euro Area countries, of which more than 110 banks were identified as O-SII. To identify the medium-term effects on banks' risk-taking behaviour and credit supply two specifications are proposed. The upper panel presents the estimate for the impact of the identification of O-SII, controlling only for non-observable banks' characteristics and quarter fixed effects. The lower panel shows the estimates when the lagged values of the yearly credit-to-GDP gap, the distance from the current and required CET1 ratio,[31] and the risk-weights density are also controlled. Moreover, the explanatory variables related with the profile of current and future O-SII requirements (one month, one year, and 5 years ahead) were included in our specifications.

Table 6 presents the results for credit supply, defined as quarterly credit growth rate as a change in the log of a banks' credit volume. The estimates shows that O-SII banks do not reduce their supply of credit. Exposures to economic sectors do not differ between banks identified as O-SII and others. The results hold if country- and bank-specific control variables are included, in order to address concerns that differences in banks' characteristics are correlated with changes in credit demand. Table 7 presents the results for risk-taking, defined as quarterly changes in risk-weights density. The estimates show that if observable and non-observable characteristics of banks, countries and time fixed effects are controlled, banks identified as O-SII compared to those just below the threshold reduce their risk-taking by 2 up to 4 percentage points in the households and financial sectors. [32]

In order to test the robustness of our results vis-à-vis the optimal bandwidth, the treatment effects using different bandwidths are re-estimated, by using identical controls and fixed effects. Table A3 confirms the previous results as no significant treatment effects are present over a wide range of different bandwidths. Our risk-taking estimates are also robust, as can be seen in Table A4, in particular a reduction of the risk-taking in the household sector is observable for a plenitude of bandwidth combinations.

[31] The regulatory CET1 ratio is computed as the one resulting from Pillar 1 and Pillar 2 requirements, capital conservation buffer, countercyclical capital buffer, global systemically important institutions and other systemically important institutions buffers and systemic risk buffer.

[32] Our outcome variables are presented in four exposure classes, namely households, non-financial corporations, non-financial private sector and financial sector, to identify the effect of the additional regulatory surcharge on each sector of the economy. Each variable is trimmed to reduce the influence of extreme values in the precision of the estimates. In each table, the coefficient on the interaction between the O-SII dummy and the post-notification dummy, along with the corresponding p-values, are presented.

Table 6: Credit Supply: Average effect of O-SII identification by economic sector

	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ*Log Credit*				
MSE-optimal bandwith	-0.005	0.017	0.013	0.01
(p-value)	0.359	0.128	0.100	0.724
Bandwith	[143, 1285]	[114, 1185]	[122, 1447]	[151, 2326]
Observations	145	116	124	153
Order of polynomial	2	2	2	2
MSE-optimal bandwith	-0.007	0.016	0.015	0.014
(p-value)	0.219	0.175	0.076	0.699
Bandwith	[116, 1044]	[93, 963]	[99, 1175]	[122, 1890]
Observations	1040	938	1043	1398
Order of polynomial	2	2	2	2
Bank fixed effect	Y	Y	Y	Y
Quarter fixed effect	Y	Y	Y	Y
Controls	None	None	None	None
	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ*Log Credit*				
MSE-optimal bandwith	-0.005	0.038	0.01	-0.044
(p-value)	0.588	0.214	0.523	0.660
Bandwith	[65, 695]	[130, 1180]	[67, 1292]	[89, 1336]
Observations	402	654	527	603
Order of polynomial	2	2	2	2
First-stage F-statistic				
MSE-optimal bandwith	-0.014	0.043	0.015	-0.022
(p-value)	0.226	0.201	0.422	0.798
Bandwith	[53, 565]	[105, 958]	[54, 1049]	[72, 1085]
Observations	341	549	454	506
Order of polynomial	2	2	2	2
Bank fixed effect	Y	Y	Y	Y
Quarter fixed effect	Y	Y	Y	Y
Controls	Country and bank controls	Country and bank controls	Country and bank controls	Country and bank controls

Notes : Estimates for the effect of O-SII identification on credit supply. The dependent variable is the quarterly growth rate as a change in the log of a banks' credit volume (from 2014:Q4 to 2017:Q4). We perform a local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at the country level. The estimates in the lower panel are conditional on the following controls: 1 year lagged value of the credit-to-GDP gap for each country, distance from the current and required CET1 ratio, banks' risk-weight density and ROA for each bank. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 7: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector

	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ*Risk-weight*				
MSE-optimal bandwith	-0.009***	0.004	-0.002	0.006
(p-value)	0.005	0.443	0.645	0.373
Bandwith	[171, 345]	[273, 1585]	[203, 1338]	[148, 928]
Observations	1007	3022	1619	1229
Order of polynomial	1	2	2	2
CER-optimal bandwith	-0.01***	0.005	-0.003	0.005
(p-value)	0.001	0.396	0.576	0.511
Bandwith	[143, 288]	[222, 1287]	[165, 1087]	[120, 754]
Observations	846	1740	1351	983
Order of polynomial	1	2	2	2
Bank fixed effect	Y	Y	Y	Y
Quarter fixed effect	Y	Y	Y	Y
Controls	None	None	None	None
	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ*Risk-weight*				
MSE-optimal bandwith	-0.029***	0.031	-0.022	-0.042**
(p-value)	0.009	0.174	0.127	0.014
Bandwith	[115, 418]	[107, 1037]	[105, 1499]	[161, 1264]
Observations	410	565	653	739
Order of polynomial	1	2	2	2
CER-optimal bandwith	-0.025**	0.035	-0.022	-0.049**
(p-value)	0.011	0.196	0.170	0.011
Bandwith	[96, 348]	[87, 843]	[85, 1218]	[131, 1027]
Observations	348	495	574	620
Order of polynomial	1	2	2	2
Bank fixed effect	Y	Y	Y	Y
Quarter fixed effect	Y	Y	Y	Y
Controls	Country and bank controls	Country and bank controls	Country and bank controls	Country and bank controls

Notes : Estimates for the effect of O-SII identification on risk-taking. The dependent variable is the quarterly change in the average risk-weight density. We perform a local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at the country level. The estimates in the lower panel are conditional on the following controls: 1 year lagged value of the credit-to-GDP gap for each country, distance from the current and required CET1 ratio, banks' risk-weight density and ROA for each bank. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

6 Conclusions

In this paper, we exploit the provision of the EU framework[33] in order to identify the causal effect of higher capital buffer requirements on banks' lending and risk-taking behaviour. According to the EU framework, the identification of the O-SII is mainly determined by a scoring process, which automatically qualifies a bank with a score above a predetermined threshold as systemically important. This scoring process allows us to exploit the discontinuity induced by the O-SII identification process. The key underlying assumption is that there exists a narrow window around the threshold such that for all banks whose scores fall within that window the assignment above or below the cutoff is probabilistic, allowing for a randomized experiment. The EU framework definitely induces a randomised experiment in a neighbourhood of the threshold. Therefore, we can identify the effect of higher capital requirements by comparing the change in the outcome of banks just above and below the cutoff.

Relying on confidential granular supervisory data, we find that O-SII banks close to the threshold slightly reduced, in the short-term, their credit supply to households and financial sectors and shifted their lending to less risky counterparts within the non-financial corporations sector. Yet, in the next three years the effect on the credit supply is attenuated.[34] The results suggest that banks, in the medium-term, constrained with higher capital buffers shifted their lending to less riskier counterparts within the financial and household sectors. Therefore, following the conclusions of Admati et al. (2018), our results suggest that banks tend to comply with higher capital requirements by dampening down their risk-weighted assets (the denominator of the capital ratio).[35] This follows the debate on how banks adjust their balance sheets in response to higher capital requirements imposed by policy regulation (see Gropp et al. (2018)). As suggested by Hanson et al. (2011) and Gropp et al. (2018), targeting the absolute amount of new capital that has to be raised instead the capital ratio could mitigate the problem of some potential optimisation of risk-weighted assets, as applied in the U.S. stress test conducted in 2009 (Hirtle et al. (2009)). However, as mentioned by Repullo (2003) capital requirements can reduce banks gambling incentives, leading to a prudent equilibrium.

Despite affecting risk-taking, and following the conclusions of Buch and Prieto (2014), the analysed policy change seem to have a limited impact on banks' credit supply. This might reflect that the activation of the buffer requirement was generally phased-in over several years, which may provide a rationale for the absence

[33] Capital Requirements Directives (CRDV) for the financial services industry and the related EBA Guidelines on the assessment of O-SII (EBA/GL/2014/10).

[34] The estimations capture an average effect, i.e. on average banks reduced their exposure to the non-financial private sector. Given the heterogeneity in banks' responses to higher capital requirements, some banks targeted the households sector and others targeted the non-financial corporates sector. This reflects different strategies through where banks can adjust their risk profile.

[35] Banks can increase their capital ratios in two different ways: they can either increase their levels of regulatory capital (the numerator of the capital ratio) or decrease their risk-weighted assets (the denominator of the capital ratio) (Gropp et al. (2018)).

of medium-term effects on the volume of credit.

This paper assesses the impact of higher capital buffers on banks' lending and risk-taking behaviour. The findings support the discussion on the short-run costs and provide policy-makers with relevant information to calibrate their policy actions. In terms of policy implications, as mentioned by Gersbach and Rochet (2017)[36] and Repullo (2003), our results show that capital requirements which target the regulatory capital ratio could have potentially a positive disciplining effect by reducing risk-taking, while having only a reduced adverse impact on the real economy.

[36] These authors examine theoretically the effects of more stringent capital regulation on bank asset portfolio risk. Their analysis shows that for a value-maximizing bank incentives to increase asset risk decline as its capital increases.

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Appendix A.

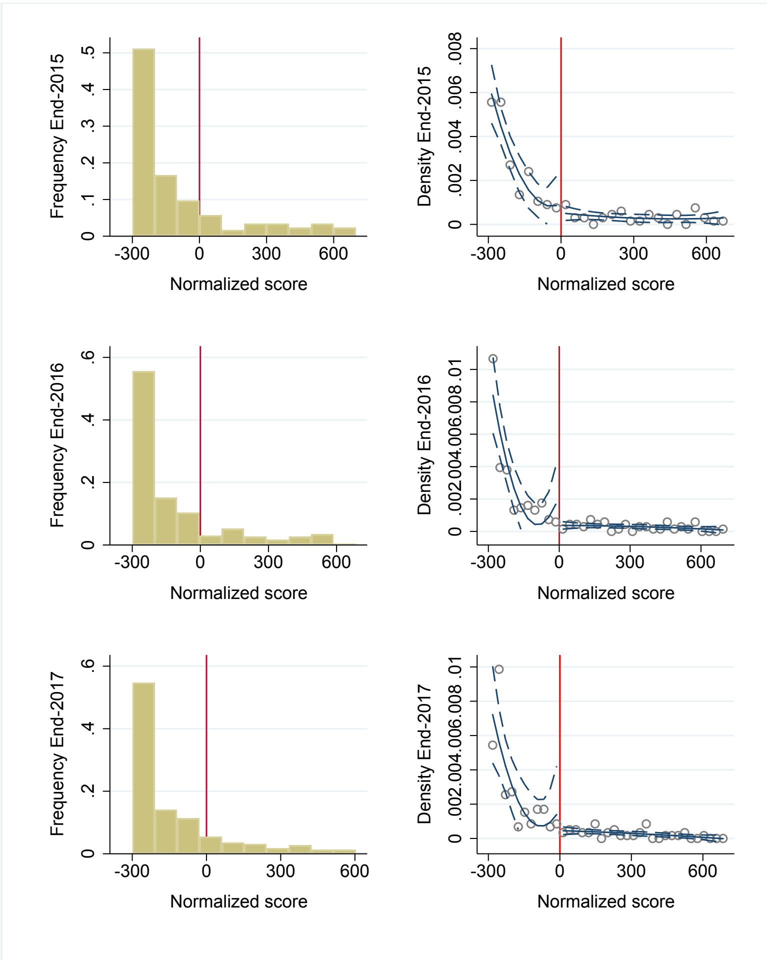
Table A1: Additional descriptive statistics

		Not O-SII		O-SII	
		Pre-notification	Post-notification	Pre-notification	Post-notification
ΔLog Credit (quarterly)					
Households	*Min*	-8.908	-8.668	-2.477	-3.268
	p10	-0.045	-0.038	-0.035	-0.028
	p90	0.061	0.053	0.035	0.039
	Max	6.253	6.441	0.853	3.936
Non-financial corporations	*Min*	-8.422	-14.45	-1.203	-2.565
	p10	-0.119	-0.113	-0.061	-0.06
	p90	0.127	0.123	0.069	0.064
	Max	9.289	9.321	2.174	1.086
Non-financial private sector	*Min*	-8.673	-9.084	-1.221	-0.9
	p10	-0.046	-0.044	-0.035	-0.035
	p90	0.068	0.057	0.046	0.035
	Max	6.042	6.138	2.174	0.785
Financial sector	*Min*	-10.071	-14.362	-1.858	-2.306
	p10	-0.285	-0.312	-0.227	-0.229
	p90	0.261	0.318	0.164	0.176
	Max	8.307	11.321	2.442	2.29
ΔRisk-weights (quarterly)					
Households	*Min*	-119.604	-0.841	-0.628	-2.432
	p10	-0.009	-0.009	-0.013	-0.011
	p90	0.007	0.006	0.008	0.008
	Max	30.886	0.868	0.699	1.466
Non-financial corporations	*Min*	-1.225	-4.447	-0.279	-1.179
	p10	-0.03	-0.027	-0.028	-0.019
	p90	0.02	0.03	0.018	0.017
	Max	0.944	5.101	0.409	0.7
Non-financial private sector	*Min*	-6.817	-1.486	-0.251	-0.297
	p10	-0.022	-0.021	-0.022	-0.017
	p90	0.02	0.017	0.014	0.012
	Max	1.396	1.311	0.134	0.362
Financial sector	*Min*	-0.958	-1.642	-0.52	-0.538
	p10	-0.03	-0.03	-0.031	-0.035
	p90	0.03	0.022	0.022	0.034
	Max	1.709	0.991	0.271	0.54

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 credit growth rate is the change in the log of a banks' credit volume. The quarterly changes are in percentage points.

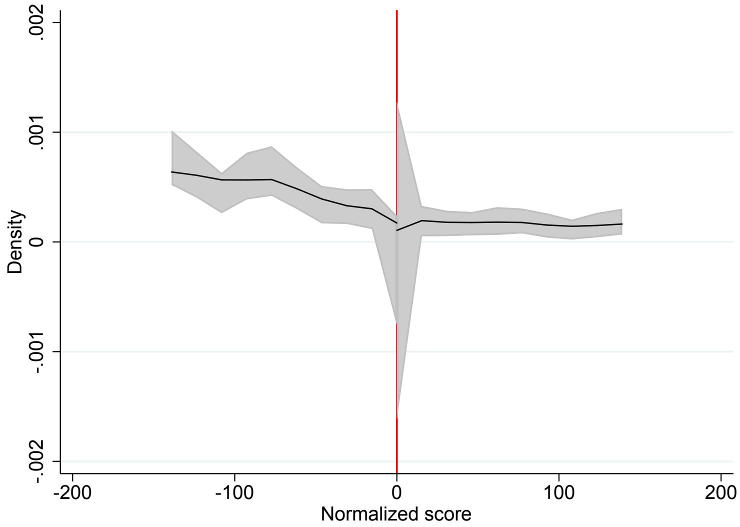
1 year lagged value of the credit-to-GDP gap for each country, distance from the current and required CET1 ratio, banks' risk-weight density and ROA for each bank.

Figure A1: Cross-sectional test of continuity of the score's density



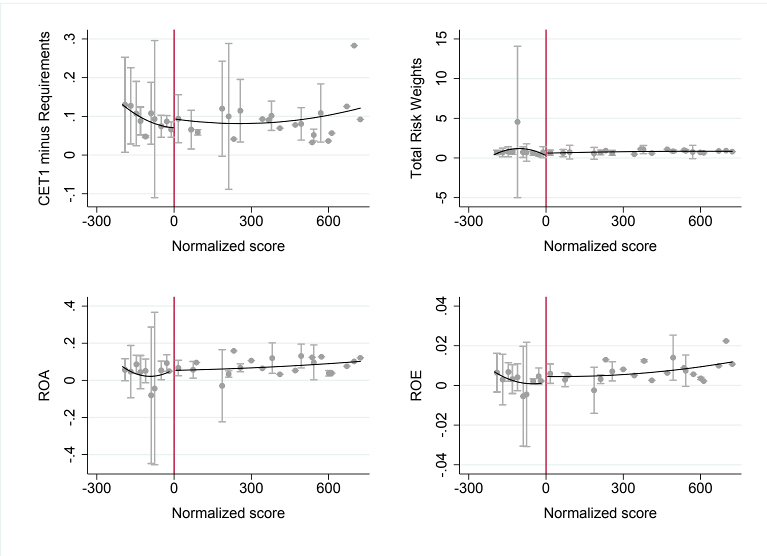
Notes: Test of continuity at the threshold. The graphs on the right-hand side exhibit the frequency of scores, while the graphs on the left-hand side represent the McCrary test of density continuity. A weighted kernel estimation performed separately on each side of the cutoff is used

Figure A2: Cross-sectional test of continuity of the score's density



Notes: Test of continuity or not manipulation of the score at the threshold (Cattaneo, Jansson and Ma (2018)). For this test, we considered the scores at the end of 2015, 2016 and 2017. The test statistic is constructed using a polynomial of order 2. The manipulation test is to 0.11 with a p-value of 0.91. Therefore there is no statistical evidence of systematic manipulation of the running variable.

Figure A3: Test of continuity of the covariates (End-2015)



Notes: Test of continuity or similarity for covariates (Skorovron, Titiunik, 2015). For this test, we consider the scores and the covariates at the end of 2015. The test statistic is constructed using a polynomial of order 2.

Table A2: Test of continuity of the covariates at the threshold (end-2015)

	Common Equity Tier 1		Total Risk-Weights		Return-on-Assets		Return-on-Equity	
	Current	1 Year Lagged	Current	1 Year Lagged	Current	1 Year Lagged	Current	1 Year Lagged
Point Estimator	0.076	0.032	0.032	-0.104	0.009	0.012	0.046	0.179
P-value	0.337	0.622	0.966	0.528	0.937	0.418	0.293	0.44
Polynomial	1	1	1	1	1	1	1	1
Bandwidth	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]
Number of observations	[42, 55]	[40, 56]	[42, 55]	[40, 56]	[37, 39]	[34, 37]	[37, 39]	[34, 37]
Point Estimator	0.106	0.021	0.016	0.605	-0.029	0.01	-0.693	0.061
P-value	0.42	0.523	0.794	0.923	0.181	0.887	0.151	0.274
Polynomial	2	2	2	2	2	2	2	2
Bandwidth	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]	[-200, 900]
Number of observations	[42, 55]	[40, 56]	[42, 55]	[40, 56]	[37, 39]	[34, 37]	[37, 39]	[34, 37]

Notes: The selected bandwidths are based on the optimal bandwidth selected for the estimations. The results are robust if we use the optimal bandwidth in the equation used for testing the continuity of the covariates.

Table A3: Credit supply: Average effect of O-SII identification by economic sector for different bandwidths

Households		Left Bandwidth									
		50	100	150	200	300	400	500	600	700	800
Right Bandwidth	50	0.22	0.03	0.22	-0.14	-0.19	0.06	0.02	0.01	0.00	-0.01
	100	-0.09	0.50	0.11	0.07	0.05	0.05	0.03	0.02	0.02	0.01
	150	0.19	0.01	0.04	0.02	0.00	-0.01	-0.01	-0.01	-0.01	-0.02
	200	-0.13	-0.01	0.04	0.03	0.01	-0.01	-0.02	-0.02	-0.02	-0.02
	250	-0.11	-0.04	0.03	0.02	0.00	-0.01	-0.02	-0.02	-0.02	-0.03
	300	-0.05	-0.05	0.00	0.00	-0.02	-0.03	-0.03	-0.03	-0.03	-0.04
Non-financial corporations		Left Bandwidth									
		50	100	150	200	300	400	500	600	700	800
Right Bandwidth	50	-0.41	-0.06	-0.21	0.33	0.46	-0.01	0.03	0.03	0.02	0.02
	100	-0.04	-0.19	-0.12	-0.05	-0.01	0.07	0.07	0.07	0.06	0.07
	150	-0.22	-0.04	-0.13	-0.05	0.00	0.05	0.06	0.06	0.06	0.06
	200	0.49	0.02	-0.17	-0.11	-0.07	-0.01	0.01	0.02	0.02	0.02
	250	0.16	0.00	-0.17	-0.11	-0.06	-0.02	0.00	0.01	0.01	0.01
	300	0.03	-0.01	-0.11	-0.07	-0.03	0.00	0.02	0.02	0.02	0.02
Non-financial private sector		Left Bandwidth									
		50	100	150	200	300	400	500	600	700	800
Right Bandwidth	50	-0.24	0.08	1.77	-0.09	-0.13	0.09	0.07	0.07	0.06	0.06
	100	-0.07	2.28	-0.02	-0.03	-0.02	0.00	0.00	0.00	-0.01	-0.01
	150	-0.07	0.24	-0.01	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00
	200	0.06	0.19	-0.01	-0.04	-0.04	-0.03	-0.02	-0.02	-0.02	-0.01
	250	0.09	0.16	-0.01	-0.04	-0.04	-0.03	-0.02	-0.02	-0.02	-0.01
	300	0.10	0.11	0.00	-0.03	-0.05	-0.03	-0.02	-0.02	-0.02	-0.01
Financial sector		Left Bandwidth									
		50	100	150	200	300	400	500	600	700	800
Right Bandwidth	50	0.73	-0.73	2.8	-0.03	-0.13	-0.08	-0.25	-0.31	-0.31	-0.27
	100	0.03	21.86	-0.35	-0.86	-0.6	-0.38	-0.41	-0.44	-0.44	-0.42
	150	-1.17	2.16	0.26	-0.42	-0.49	-0.37	-0.27	-0.24	-0.23	-0.2
	200	-8.79	2.16	0.24	-0.41	-0.55	-0.46	-0.31	-0.27	-0.25	-0.22
	250	43.59	2.06	0.19	-0.36	-0.46	-0.35	-0.24	-0.22	-0.2	-0.18
	300	1.40	0.92	0.02	-0.38	-0.51	-0.42	-0.3	-0.27	-0.26	-0.24

Notes : Estimates for the effect of O-SII identification on credit supply. The dependent variable is the quarterly growth rate as a change in the log of a banks' credit volume (from 2014:Q4 to 2017:Q4). We perform a local linear regressions on a second-order polynomial with a triangular kernel. Standard errors are clustered at the country level. The estimates in the lower panel are conditional on the following controls: 1 year lagged value of the credit-to-GDP gap for each country, distance from the current and required CET1 ratio, banks' risk-weight density and ROA for each bank. Bank- and quarter-specific fixed effects are used. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table A4: Risk-taking (risk-weights): Average effect of O-SII identification by economic sector for different bandwidths

Households		Left Bandwidth												
			100	150	200	300	400	500	600	700	800	900	1000	1100	1200
Right Bandwidth	50	0.016	-0.023	0.011	0.109	-0.058	-0.052 ***	-0.047 **	-0.045	-0.044	-0.044	-0.046	-0.046	-0.046	-0.045
	100	-0.062	-0.11	-0.105	-0.077	-0.066*	-0.08	-0.071	-0.067	-0.065	-0.064	-0.065	-0.063	-0.061	-0.059
	150	-0.116*	-0.124*	-0.099 **	-0.083 **	-0.079 **	-0.085*	-0.078*	-0.075*	-0.074*	-0.073*	-0.072*	-0.07*	-0.068*	-0.066*
	200	-0.138	-0.162	-0.121	-0.094*	-0.088*	-0.089*	-0.081*	-0.08	-0.078	-0.077*	-0.077*	-0.074*	-0.071*	-0.069*
	250	-0.131*	-0.159	-0.12	-0.096*	-0.089*	-0.09*	-0.084*	-0.083	-0.082	-0.081	-0.08*	-0.077*	-0.074*	-0.071*
	300	-0.099*	-0.152	-0.11	-0.086	-0.079	-0.08*	-0.076*	-0.076	-0.076	-0.075	-0.074*	-0.071*	-0.067*	-0.065*

Non-financialcorporations		Left Bandwidth												
			100	150	200	300	400	500	600	700	800	900	1000	1100	1200
Right Bandwidth	50	81.71	0.04	-0.21	-0.03	0.01	-0.01	0	-0.01	0.01	0.01	0.01	0.02	0.02	0.02
	100	0.08	2.86	0.46	0.22	0.12	0.08	0.08	0.07	0.09	0.1	0.1	0.1	0.1	0.09
	150	0.17	0.18	0.14	0.13	0.11	0.08	0.07	0.06	0.07	0.07	0.07	0.07*	0.07*	0.06*
	200	-0.52	0.11	0.14	0.16	0.17	0.14	0.11	0.1	0.1	0.1	0.09	0.09	0.09*	0.08*
	250	-0.04	0.14	0.14	0.17	0.19	0.15	0.13	0.12	0.12	0.11	0.11	0.1	0.1*	0.1*
	300	0.17	0.14	0.12	0.14	0.18	0.15	0.13	0.13	0.12	0.12	0.11	0.11	0.11	0.1

Non-financialprivate sector		Left Bandwidth												
			100	150	200	300	400	500	600	700	800	900	1000	1100	1200
Right Bandwidth	50	0.11	0.02	0.06	0.05	0.09	-0.06	-0.07	-0.07	-0.07	-0.07	-0.08	-0.09	-0.09	-0.09
	100	-0.08 **	-0.29	-0.43	-0.31	-0.22	-0.13*	-0.12	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11
	150	-0.31	-0.15	-0.22	-0.24	-0.22	-0.18	-0.14	-0.13	-0.13	-0.12	-0.12	-0.12	-0.12	-0.12
	200	-0.38	-0.21	-0.22	-0.24	-0.24	-0.19	-0.15	-0.14	-0.13	-0.13	-0.13	-0.13	-0.12	-0.12
	250	-0.46	-0.27	-0.23	-0.23	-0.23	-0.17	-0.14	-0.13	-0.12	-0.12	-0.11	-0.11	-0.11	-0.11
	300	-0.2	-0.19	-0.19	-0.21	-0.24	-0.19	-0.16	-0.15	-0.14	-0.13	-0.13	-0.13	-0.12	-0.12

Financial sector		Left Bandwidth												
			100	150	200	300	400	500	600	700	800	900	1000	1100	1200
Right Bandwidth	50	-0.39	-0.03	-0.11	-0.03	0.03	0.03	-0.04	-0.06	-0.07	-0.09	-0.08	-0.07	-0.07	-0.06
	100	-0.02	0.81	-0.23	-0.07	-0.08	-0.04	-0.06	-0.07	-0.08	-0.09	-0.09	-0.08	-0.08	-0.08
	150	0.31	-0.28	-0.09	-0.1	-0.15	-0.14	-0.12	-0.12	-0.12	-0.12	-0.11	-0.1	-0.1	-0.1
	200	-3.55	-0.28	-0.06	-0.06	-0.1	-0.11	-0.09	-0.09	-0.09	-0.09	-0.09	-0.08	-0.08	-0.08
	250	-3.29	-0.29	-0.04	-0.04	-0.07	-0.08	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.06
	300	-0.33	-0.15	-0.01	0	-0.03	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05

Notes : Estimates for the effect of O-SII identification on risk-taking. The dependent variable is the quarterly change in the average risk-weight density. We perform a local linear regressions on a second-order polynomial with a triangular kernel. Standard errors are clustered at the country level. The estimates in the lower panel are conditional on the following controls: 1 year lagged value of the credit-to-GDP gap for each country, distance from the current and required CET1 ratio, banks' risk-weight density and ROA for each bank. Bank- and quarter-specific fixed effects are used. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

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