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

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Abstract

We study the impact of higher bank capital buffers, namely the other systemically important institutions (O-SII), on lending and banks' risk-taking behaviour at different horizons from the first implementation. Although there is already evidence that higher capital buffers constrain credit supply and might lead to bank risk-shifting in the short-term, in this paper we shed more light on the medium-term effects of these type of policy measures. Relying on 2014 to 2017 confidential granular supervisory data, we find that O-SII banks reduced their credit supply to households and financial sectors in the short-term, shifting their lending to less risky counterparts. In the medium-term the reduction in credit supply becomes not significant from an economic perspective, whereas there is evidence that banks shift their lending to less risky borrowers *within* sectors. Our findings support the hypothesis that the implementation of higher capital buffers could have a positive disciplining effect by reducing banks' risk-taking. At the same time, there is evidence of only a reduced adverse impact on the real economy through a temporary decrease in credit supply restricted to the moment when there is a tightening of the macroprudential policy.

Keywords: Macroprudential policy, Systemic risk, Capital buffers, Bank risk-shifting, Credit supply
JEL Codes: E44, E51, E58, G21, G28

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1 Introduction

The literature on the effectiveness of macroprudential instruments has grown rapidly and first evidences were found regarding the impact of policy decisions (implying higher capital requirements for banks) in the short-term. This provides only limited guidance for policy measures aiming to shape the banking system in the medium- and long-term horizon. Part of the explanation is the limited experience with implementing macroprudential policy measures. Some measures - widely considered 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 was previously considered sufficient to ensure macroeconomic and financial stability. The recent financial crisis 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)). Such assessment requires an understanding of each instrument's effectiveness in limiting systemic risk and of the interactions between policy instruments (e.g. macroeconomic and macroprudential ones). 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)). Claessens et al. (2013) and the IMF Macroprudential Policy Survey database later complemented the survey.[2]

Following recent progress, a strand of literature has attempted to shed light on the link between capital regulation and economic growth.[3] 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 may impact the real economy. 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) at the first introduction of the policy but also some years after.[4] In particular, this paper for the first time highlights the impact across economic sectors and the medium-term effects of newly introduced macroprundential policies.

Since 2015, authorities identified more than 110 banks as O-SII, charging some with additional CET1 capital requirements. While the policy implementation differed across countries in calibration methodologies and phase-in arrangements, in most cases the identification of O-SII was made following the European

[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 use prudential instruments in practice throughout the business and financial cycles.

[3] Recent progress on data collection includes 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 usage intensity of several common prudential tools, considering both macro-prudential and micro-prudential objectives. Budnik and Kleibl (2018) built a new comprehensive dataset on policies of a macroprudential nature in the banking sectors of the 28 member states of the European Union (EU) between 1995 and 2014. Konietschke et al. (2022) find that banks participating in the stress tests reallocate credit away from riskier borrowers and towards safer ones in the household sector, making them in general safer but also less profitable. This is especially the case for the set of banks part of the Supervisory Review and Evaluation Process with undisclosed stress tests, which were also not disclosing their Pillar 2 Requirements voluntarily.

[4] 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.

Banking Authority (EBA) guidelines (EBA (2014)). Under these guidelines, each bank receives a score based on four mandatory indicators proxying its systemic importance. Banks with a score above a country-specific threshold are automatically designated as O-SII.[5] 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.[6] By exploiting the discontinuity induced by the EBA selection rule, we can estimate the impact of an increase of 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, at different time horizons with respect to the date of first policy decision.

In the short-term, in line with previous evidence in the literature,[7] we find that banks designated as O-SII reduced, their credit supply to households and financial sectors. However, such reduction wanes in the medium-term, as banks shift 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 introducing the O-SII surcharge had a positive disciplining effect. This new results are in line with some theoretical findings on the impact of capital-based regulation. For instance, Furlong and Keeley (1989) incorporate the option-value of deposit insurance into a state-preference model and show that a value-maximising risk-neutral bank responds to an exogenous increase in bank capital by reducing the level of riskier assets. Hence, our analysis indicates a non-significant impact on credit growth for banks close to the threshold in the medium run. Nevertheless, at the inception of the O-SII's framework, the tightening of capital requirements negatively affected lending to some counterparties. These new results allow to understand better the effectiveness of macroprudential policies in a longer-term horizon.

Our paper belongs to two strands of literature. First of all, it is part of the empirical literature which analyses the effect of capital policy regulation on credit supply.[8] Second, our paper contributes to the

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

[6]As referred by Gropp et al. (2018) and Behn and Schramm (2021), banks can increase their capital ratios in two different ways: they either increase their equity (the numerator of the capital ratio) or decrease their risk-weighted assets (the denominator of the capital ratio). We focus our analysis on the denominator of the capital ratio in order to assess banks' lending behaviour.

[7]Peek and Rosengren (1997) find that 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 per cent in the level of lending after 16 quarters. De Jonghe et al. (2016) find that higher capital requirements correspond to balance sheet adjustments and 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 households. 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 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 remain 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.

[8]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 per cent increase in CET1 requirement had an annualized loan growth (over nine months) of 1.2 per cent lower than unaffected banks. Gropp et al. (2018) study the impact of higher capital requirements on banks' balance sheets and their 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

literature on the effect of policy actions on banks' risk-taking. The confidential supervisory dataset provides a direct measure of banks' risk-weight density across all euro-area banking systems, including the standardised approach and the internal ratings-based approach (IRB). This allows us to quantify the extent of derisking without making assumptions on the risk-weights structure of the bank.[9]

Recently, Degryse et al. (2021) document an increase in collateralization for loans to firms. Relative to them, we do not restrict our analysis to corporations, but we look at a broader spectrum of sectors. Overall, we find evidence of a mechanism similar to theirs being at play in the household sector, with O-SII banks significantly adjusting their risk profile. Under the standardised approach, regulatory retail portfolios generally carry a risk-weights of 75%. By contrast, loans secured by residential property only carry a risk-weight of 35%. This suggests that banks constrained with an OSII requirement may have achieved a reduction in risk-weights in the medium-term by increasing the share of secured loans. Leveraging information on collateralized exposures, we do not find evidence in favor of this hypothesis. The reduction highlighted in the medium-term perspective may therefore reflect changes in lending standards and in the risk assessment of banks, rather than an increase in collateralization. Bidder et al. (2021) focus on the US banking sector and exploit a very different shock, namely the oil price decline in 2014. This kind of shock may have impacted borrowers very differently depending on the economic sector.[10] We do not find evidence that the policy affected significantly corporate lending - a finding which is robust to (i) the time-horizon (short- or medium-term) and (ii) the type of adjustment (credit volume vs risk-weights). One possible rationale behind the different findings relies on the fact that bank lending rates to corporates are higher than the lending rates to households, making the corporate segment relatively more profitable. The absence of a significant effect on corporate lending may hence reflect banks' effort to keep sufficiently high returns as weak profitability has been a key feature of the European banking industry since mid-2012.

In a nutshell, our results show that banks identified as O-SII reduced, in the short-term, their credit supply to the households and financial sectors and there is evidence that they shifted their lending to less risky counterparts within those sectors. Banks deleverage and derisk by dampening down the risk-weighted assets (both in amounts and risk-weights) to comply with the higher capital buffer requirement. As a result, banks lending to household and financial sectors decreased together with the risk of the borrowers. We can explain banks' re-balancing behaviour for lending and risk-taking in the households and financial sectors by their willingness to keep the level of profitability (which is higher for the corporates segment given higher bank lending rates). Moreover, we observe a short-lived credit contraction and a risk-averse shift toward safer borrowers within sectors, allowing banks to comply with novel capital regulation while

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. The 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.

[9] 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 impact banks' risk-taking significantly. As Borio and Zhu (2012) and Adrian and Shin (2009) showed, in the run-up to the crisis, a prolonged low interest rate environment might fuel an asset price boom and lead banks to take excessive risks and leverage. Dell'Ariccia et al. (2014) find that the level of leverage determines the strength of the risk-shifting effect and that the impact of monetary policy on risk-taking depends on the level of bank capitalization. Admati et al. (2018) suggest that the banks' shareholders prefer to increase their capital ratios by reducing risk-weighted assets instead of raising new capital. More recent contributions highlight the impact of higher capital requirements (Degryse et al.,2021) or capital losses (Bidder et al., 2021) on the risk profile of banks. Degryse et al. (2021) focus on Portuguese banks and study the impact of the 2011 EBA capital exercise. Instead, we leverage information on the whole euro area banking system, covering a more representative sample. In addition, the effect of the capital exercise could reflect the relative magnitude of the overall capital shortfall and the specificities of the Portuguese banking system, such as relatively high net direct sovereign exposures.

[10] They identified government-backed loans as those less affected.

preserving profitability. At first glance, the reduction in risk taking was not related to an increase of collateralization but more probably to an improvement in credit quality and a shift in the loan supply towards safer counterparties.

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.[11] 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, established in the guidelines, is based on four mandatory indicators that should capture the systemic footprint of each institution (see Table 1).[12] 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; they may consequently adjust the threshold, making it higher (maximum 425 basis points) or lower (minimum 275 basis points).[13]

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

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

[12] The four criteria each consist of one or more mandatory indicators. All criteria should be weighted equally at a weight of 25 per cent. The indicators within each criterion should be weighted equally relative to the other indicators within the respective criterion.

[13] In 2015, most 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.

The second step of the procedure entails a 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.[14] This secondary supervisory judgment is typically applied to identify (as O-SIIs) banks that were not identified based on automatic score. Nevertheless, only in a few cases this supervisory judgment was applied to reverse an O-SII identification for a bank above the threshold, due to national specificities, a small and concentrated banking system or ongoing liquidation (Table 2). 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 some jurisdictions subsidiaries of Significant Institutions (SIs) domiciled in other SSM countries were identified as O-SII, in the analysis we take a consolidated perspective and we do not include subsidiaries of banks that are identifies as O-SIIs.

From the 1st of January 2016, national authorities started to implement stricter capital requirements, typically in the form of CET1 capital buffers.[15] 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 valuation of O-SII buffers.[16] 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 per cent 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 measure's introduction are 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.[17] In addition, different multi-year linear phase-in periods have been adopted. Estonia, Finland, Lithuania and Slovenia are the only countries that already required a fully loaded implementation from the first year.

[14]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.

[15]A few countries complemented the O-SII surcharge introducing of the systemic risk buffer.

[16]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.

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

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.

3 Data

In order to assess the effect of the implementation of the O-SII framework on credit supply and risk-taking, the analysis relies two main sources of information. First, the notifications that national authorities - in charge of identifying other systemically important institutions (O-SIIs) - shall send to the Commission, the ESRB, EBA, and ECB.[18] The notifications include the annual assessment by national authorities, which includes the required capital buffer's level and the date of notification, of publication and of implementation of the policy measure. In the notification the score of large share of banks in the jurisdiction was included. Complementing 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.[19] Second, the supervisory reporting (i.e. Common Reporting Framework (COREP) and Financial Reporting Framework (FINREP)) of SSM (Single Supervisory Mechanism) banks. The confidential supervisory 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. This latter source of information have also a breakdown of exposures by obligor level of riskiness (grades or pools), which allows for assessing the risk shifting across different buckets of obligor grades [20].

Out of almost 1,300 entities, more than 110 were identified as O-SII at least once during the period

[18] Based on Article 131(7) of the Directive 2013/36/EU (CRD IV) National Authorities should notify at different stages of the decision process ECB, EBA and ESRB.

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

[20] See Corep template 8.02 buckets of borrowers with the same level of risk

considered,[21] the vast majority of which qualifies as Significant Institutions (SI) or subsidiaries domiciled in other Member States. The analysis considers banking groups and banks at the highest level of consolidation within SSM.[22]

Table 3: Descriptive statistics

	Not O-SIIs		O-SIIs	
	Total	of which: close to the threshold	Total	of which: close to the threshold
Δ *Log Credit (quarterly)*				
Households	0.058	0.118	-0.006	-0.092
	(0.51)	(0.146)	(0.31)	(0.7)
Non-financialcorporations	0.02	-0.012	-0.044	-0.088
	(0.624)	(0.513)	(0.377)	(0.371)
Financial sector	-0.088	-0.171	-0.102	-0.18
	(0.794)	(0.576)	(0.415)	(0.453)
Δ *Risk Weights*				
Households	-0.033	0.03	-0.035	0.007
	(0.281)	(0.055)	(0.109)	(0.115)
Non-financialcorporations	-0.006	-0.058	0.0026	0.02
	(0.203)	(0.477)	(0.118)	(0.102)
Financial sector	-0.071	0.002	-0.045	-0.028
	(0.598)	(0.361)	(0.225)	(0.188)

Notes: The reference date is the quarter following the first decision regarding the identification of O-SII banks.
Mean values are computed separately for banks below and above the threshold. Being close to the thresholds refer to the intervals used for the cross-sectional regression (see Table 4).
Standard deviations are reported in parenthesis.

Table 3 presents, for each variable of interest, the mean and the standard deviation for banks below and above the threshold and for those close to the threshold. It is important to notice that banks above (below) the threshold are not statistically different from the overall set of (Not) O-SII banks. Yet, the variability within each group is sizeable and looking to Figure 1 and 2 there some outliers. This evidence supports the conjecture that the potential causal effect measured at the threshold can be rappresentative of the average causal effect for the whole sample of banks.

In term of the country distribution the initial sample covers the 19 countries in the SSM while selecting the banks close to the threshold the coverage across countries reduces to around 13 countries.[23]

MAYBE TO BE DROPPED[24]

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 indentifying a bank as an O-SII on lending and risk-taking behaviour, we consider different indicators using the exposure at default (EAD) as a measure of total exposures.[25] To

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

[22] Banks belonging to G-SIBs domiciled in SSM are consolidated within the parent companies, the European subsidiaries of foreign banking groups are excluded from the sample.

[23] DESCRIBE IN DETAILS WHICH COUNTRIES DEPENDING ON THE CHOOSEN DEPENDENT VARIABLE

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

[25] Exposures are also analyzed in order to assess other events, such 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

quantify changes in levels of banks' lending, the change in the natural logarithm of a banks' total exposures is calculated.[26] To assess banks' risk-taking, the change in the average risk-weights or risk-weighted asset densities is considered.[27] 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 to external ratings or level of collateralization, 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.[28]

4 The empirical model

4.1 Identification strategy

Determining the effect of identifying a bank as systemically important and introducing higher capital requirements on banks' credit supply and risk-taking behaviour is challenging. In particular, 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.[29] To address these challenges, we rely on a peculiarity of the institutional framework, namely 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 identifying O-SII establish a scoring process based on four mandatory indicators: size,

(LTRO) program of the European Central Bank (ECB) (Van Rixtel and Gasperini (2013)). The EAD might be considered 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 credit conversion factors).

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

[27] 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).

[28] Risk-weights depend on the probability of default (PD) and the type of 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.

[29] 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 adopting the measure.

importance, complexity/cross-border activity and interconnectedness. Considering these criteria, national authorities assign to each bank under their jurisdiction a score that should represent its systemic footprint within the national banking system. Most crucially, institutions with a score equal to or higher than a certain threshold are automatically identified as O-SII.

Although supervisory judgment complemented the automatic calculation, the O-SII framework provides a natural setting for a regression discontinuity design.[30] This strategy exploits both the policy change and the discontinuity induced by the O-SII identification process. The key underlying assumption is that a window around the threshold exists such that the assignment above or below the cutoff is probabilistic, and the outcomes depend directly on the score.[31] 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 $I_{i,t} = 0$ 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.[32] 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 notify their decision to the ECB.[33] After the notification is issued (i.e. for $t \geqslant \tau$), the treatment status $I_{i,t}$ changes, where banks

[30] Thistlethwaite and Campbell (1960) and Lee and Lemieux (2010) Introduced these designs in the evaluation literature. 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) uses the regression discontinuity designs for evaluating causal effects of interventions, where assignment to a treatment is determined at least partly by the value of observed covariates lying on either side of a fixed threshold.

[31] 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 on the score.

[32] Usually $\tau\,(t)$ does not coincide with when the policy decision is implemented; for simplicity we use the same nomenclature for the date of effectiveness and the date of reference of the score.

[33] 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,

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, we assume 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 be obtained by estimating the following regression model in an interval around the threshold. The expected value of the outcome variable on the left ($E[Y_i(0)|X_i = x]$) and on the right of the threshold ($E[Y_i(1)|X_i = x]$] can be approximated by a polynomial function of the score. In particular, following Cattaneo, Idrobo and Titiunik (2017a,b), we will use a local polynomial estimator. We estimate a regression equation using only observations near the threshold, separately for control and treatment units. In particular we use observations that are between $c - h$ and $c + h'$ where $h > 0$ and $h' > 0$ define the bandwidth that determines the size of the neighborhood around the threshold. Within the bandwidth, it is common to use a weighting scheme to ensure that the observations closer to the threshold receive more weight than those further away to aim to a more precise estimate of the treatment effect at the cutoff.[34]

Therefore, two local weighted regressions are estimated respectively for the observations above and below the threshold:

$$\mu_-(S^*_{i,t}) = E[Y_{i,t}(0)|X_{i,t} = x] = \mu_{-,0} + \mu_{-,1}S^*_{i,t} + \mu_{-,2}S^{*2}_{i,t} + ... + \mu_{-,p}S^{*p}_{i,t}$$
$$\mu_+(S^*_{i,t}) = E[Y_{i,t}(1)|X_{i,t} = x] = \mu_{+,0} + \mu_{+,1}S^*_{i,t} + \mu_{+,2}S^{*2}_{i,t} + ... + \mu_{+,p}S^{*p}_{i,t}$$

where $S^*_{i,t}$ is the distance from threshold (i.e. $S^*_{i,t} := S_{i,\tau_{c(i)}} - THOLD_{c(i),\tau_{c(i)}}$) and $X_{i,t}$ is the vector of controls that includes the lagged value of CET1 minus the associated capital requirement (i.e. 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.

The treatment effect at the threshold point estimate is $\hat{\tau}_{TEAT} = \mu_+(S^*_{i,t}) - \mu_-(S^*_{i,t})$ for $S^*_{i,t}$ close to zero.

To implement the local polynomial approach, we need to choose the polynomial order and the weighting scheme. For the weighting scheme, we use a triangular kernel function that assigns zero weight to all observations with score outside the interval $[c+h; c+h']$, and positive weights to all observations within this interval. The weight is maximized at the threshold and declines symmetrically and linearly as the value of the score gets farther from the cutoff.

Regarding selecting the order of the polynomial, a polynomial of order zero would not be appropriate to estimate the treatment effect at the threshold. Increasing the order of the polynomial generally improves the accuracy of the approximation at the cost of increasing the variability of the treatment effect estimator. High-order polynomials can indeed lead to over-fitting the data and unreliable results near boundary points.[35] Combined, these factors have led researchers to prefer the local linear or quadratic RD estimator.[36]

Regarding the bandwidth, we rely on a data-driven selection approach to avoid specification searching

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.

[34]The weights are determined by a so-called kernel function.

[35]See Gelman and Imbens (2018) for the risk of selecting high-order polynomial.

[36]See Pei et al. (2018), where the authors propose and test an order-selection procedure.

and ad-hoc decisions. Most bandwidth selection methods try to balance the bias-variance trade-off; for example, a smaller bandwidth will reduce the misspecification error of the local polynomial approximation and simultaneously increase the estimated coefficients's variance, as fewer observations will be available for estimation. We will rely on two of the most popular approaches: The first seeks to minimize the Mean Squared Error (MSE) of the local polynomial RD point estimator given a choice of polynomial order and a weighting scheme.[37] The second chooses the bandwidth aiming to minimize an approximation of the confidence interval's coverage error (CER). Alternatively, a global polynomial approach can be pursued estimating a high order polynomial[38] and considering all the observations.

We start from estimating the short-term effects of higher capital buffers, focusing on the first quarter following the identification of O-SII banks and employing a pooled regression under the assumptions of linear effect of the controls:

$$\begin{aligned}Y_{i,t} = \mu_{-,0} + \mu_{-,1} S^{*}_{i,t} + \mu_{-,2} S^{*2}_{i,t} + ... + \mu_{-,p} S^{*p}_{i,t} + \\ +(\hat{\tau}_{TEAT} + \beta_{+,1} S^{*}_{i,t} + \beta_{+,2} S^{*2}_{i,t} + ... + \beta_{+,p} S^{*p}_{i,t}) I_{i,t} \\ +\beta_3 X_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{1}$$

where $I_{i,t}$ is the dummy for banks identified as O-SII and the treatment effect at the threshold point estimate is $\hat{\tau}_{TEAT}$. When focusing on the medium run effect of the macroprudential policy, we use a longitudinal dataset where we control for time fixed effect (u_t) and bank fixed effect (η_c).[39] The inclusion of bank and time fixed effects increases the efficiency of the estimate (Calonico et al., 2018, Petterddon-Lidbon, 2008). Adding these fixed effects also reflects the rich nature of our panel data, which allows us to control for changes in credit demand (Borio and Gambacorta, 2017) and for all non-bank characteristics that are time-invariant, as macroeconomic factors that affect all banks in the same manner. As a robustness check, we estimate the equation adding a fixed effect on the country of the borrower to better control for credit demand factors:

$$\begin{aligned}Y_{i,t} = \mu_{-,0} + \mu_{-,1} S^{*}_{i,t} + \mu_{-,2} S^{*2}_{i,t} + ... + \mu_{-,p} S^{*p}_{i,t} + \\ +(\hat{\tau}_{TEAT} + \beta_{+,1} S^{*}_{i,t} + \beta_{+,2} S^{*2}_{i,t} + ... + \beta_{+,p} S^{*p}_{i,t}) I_{i,t} \\ +1_t + 1_i + \beta_3 X_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{2}$$

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.[40] 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

[37]Since the MSE of an estimator is the sum of its squared bias and its variance, this approach effectively chooses h and h' to optimize a bias-variance trade-off.

[38]In using a high order polynomial Gelman and Imbens (2014) argue that estimators for causal effects based on such methods can be misleading, and they recommend using estimators based on local linear or quadratic polynomials or other smooth functions.

[39]We also run the same models adding a country/time-fixed effects and results remain unchanged.

[40]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.

the threshold to measure the causal impact of the treatment on the outcomes of interest. Following Hahn et al. (2001), let $Y^{+} = \lim_{\varepsilon \to 0^{+}} E\left[Y_{i,t} \mid S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$ and $Y^{-} = \lim_{\varepsilon \to 0^{-}} E\left[Y_{i,t} \mid S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. 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 $I^{-} = \lim_{\varepsilon \to 0^{-}} E\left[I_{i,t} | S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. 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, 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 introducing 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 bank's characteristics, on the whole national banking system, and 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, but the overall sub-scores (Table 1) will also depend on the behaviour of other banks. In order to validate this assumption, we performed different tests. First, we analyzed the distribution of the scores around the threshold 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), which assesses 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. The intuition is straightforward, if banks cannot 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 banks' lending behaviour presents several challenges. First, when capital buffers change the adjustment is often simultaneous for the entire banking system, making it practically impossible to identify any causal effects. Second, supervisors may impose bank-specific requirements based on bank characteristics; similar requirements will not be exogenous to banks' balance sheets. Third, to assess the effects of capital requirements on bank lending, it is vital to disentangle credit supply from credit demand.

We tackle these challenges by exploiting the O-SII framework 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 causal effect of identifying a bank as an O-SII and of the capital surcharges that come with the O-SII definition. Indeed, banks' discontinuous allocation to the O-SII category through a score allows us 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. We employ methods described in Calonico, Cattaneo and Titiunik (2014) and Calonico et al. (2018) to select groups of comparable observations close to the assignment threshold. Finally, we show that our results are robust to multiple specifications and polynomial orders for the bandwidth selection.

Figures 1 and 2 show the change in credit supply and risk-taking of banks around the threshold at the end of 2015. For each outcome variable, we present a scatter plot with its value against the normalized scores ($S^*_{i,t}$),[41] 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 the first representation of a potential adjustment in the outcome variables at the cutoff for banks identified as an O-SII. A visual inspection of Figure 1 and 2 does not reveal a clear discontinuity in banks' credit supply or in risk-taking, suggesting that the effect of identification may be negligible (e.g. non-financial corporation).

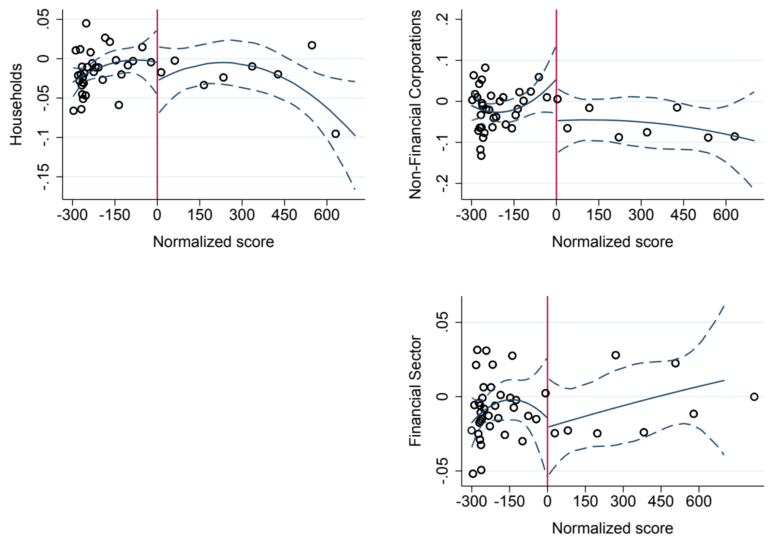
Figure 3 shows the relationship between the score of a bank and the probability of being identified as an O-SII based on the first O-SII assessment. The probability of a bank being designated as O-SII increases significantly and discontinuously if a bank receives a score above the threshold. As mentioned, several institutions below the cutoff are, nevertheless, designated as O-SII because of supervisory judgment. Figure 3 confirms the use of a fuzzy design as appropriate for the setting at hand.[42]

We report estimates for the impact of the O-SII framework on euro area's (SSM countries) banks in the first quarter after authorities' notification in Tables 4 and 5. Such Tables 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 risk-weight density. We break down our outcome variables into four exposure classes: households, non-

[41] 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.

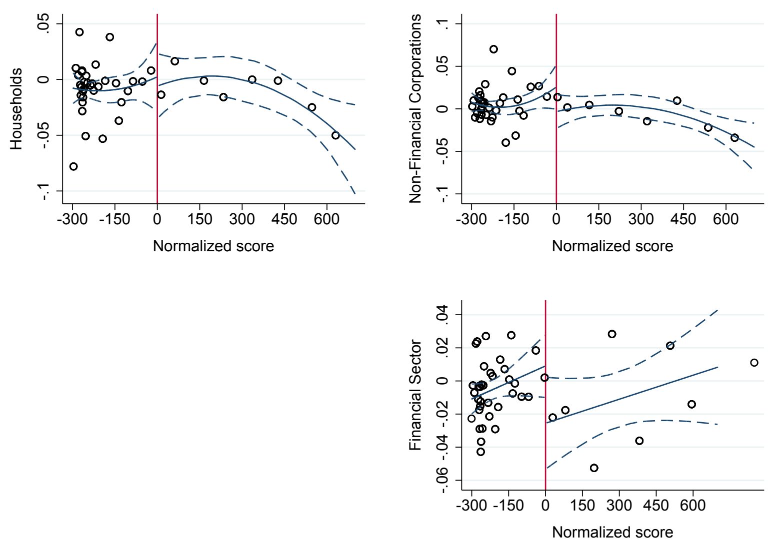
[42] Hahn et al. (2001) shows that a fuzzy regression discontinuity approach is closely related to an instrumental variable setting. For identification, it is thus important to document a strong first-stage relationship between the score of each bank (also called running variable) and the conditional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

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



Notes : The vertical axis displays the value of the credit growth for the relevant economic sector. 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 per cent confidence interval.

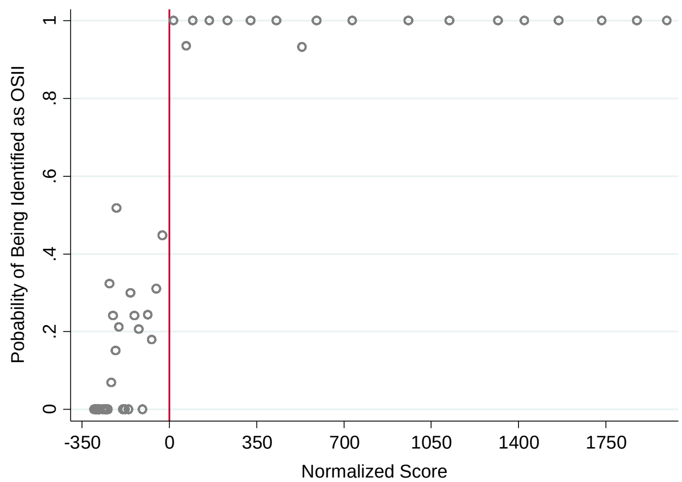
Figure 2: Risk-weights distribution of banks close to the threshold (end-2015)



Notes : The vertical axis displays the risk-weights for the relevant economic sector. 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 per cent confidence interval.

financial corporations, and the financial sector to identify the effect of the additional regulatory surcharge on each economic sector. We trim each variable at the 1st and 99th percentile to reduce extreme values' influence on estimates' precision and report O-SII dummy interaction coefficient in each table, along with

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.

the corresponding p-values.

Focusing on the first quarter following the notification, we find a significant effect on credit supply to households and financial sectors by banks identified as O-SII (Table 4). At the same time, the estimates suggest that banks identified as O-SII do not differ in terms of risk-taking from other bank (Table 5). These results are robust to the choice of the order of the polynomial (see Table A3 and A4 in the Appendix) and of the bandwidth (see Tables A7, A9, A8 and A10 in the Appendix). Letting the bandwidth vary leads to an increase in the implied impact, but also increases the volatility of the point estimates; consequently, the difference in the estimate is not statistically different to the one reported in the Tables 4 and 5.

Across specifications, we consider the following controls: the yearly lagged credit-to-GDP gap in each country, the yearly lagged distance from the actual and the required CET1 ratio[43] and the yearly lagged banks' risk-weight density, total exposures and the ratio of deposits over total assets. Moreover, we include the levels of the O-SII buffer at the end of 2015 and the end of 2020. It is worth noticing that the distance from the actual and the required CET1 ratio also captures whether the additional capital requirement can be binding for some banks. At the time of the O-SII framework first implementation, the average distance for O-SII banks was higher than five percentage points of risk-weighted assets, and, for the first percentile, this distance was well above two percentage points. This evidence suggests that the introduction of the O-SII buffer was not a binding constraint for the SSM banks.

Another key confounder we work on addressing is the (aggregate) country-specific credit cycle. For this purpose, we include the credit-to-GDP gap, defined as the difference between the ratio of total credit relative to GDP and its long-run statistical trend,[44] in our baseline regression. Adding an indicator of the financial

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

[44] Many studies have found that the credit-to-GDP gap is one of the best single early warning indicators of systemic banking crises. Accordingly, it is used in the benchmark buffer guide for the CCyB as recommended by the European Systemic Risk Board (ESRB) (see Detken et al., 2014).

Table 4: Credit Growth: Average effect of O-SII identification by economic sector (first quarter after first decision)

	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.193***	0.775	-1.276***
(p-value)	0.004	0.142	0.004
F-Statistic (first Stage)	7.611	15.671	8.490
MSE-optimal bandwith $[-h, h']$	[-66, 732]	[-194, 471]	[-91, 728]
Observations	60	124	88
Order of polynomial	2	2	2
Treatment effect	-0.197***	0.785	-1.06***
(p-value)	0.006	0.132	0.007
F-Statistic (first Stage)	9.431	12.458	8.177
CER-optimal bandwith $[-h, h']$	[-54, 597]	[-158, 384]	[-74, 594]
Observations	60	124	88
Order of polynomial	2	2	2
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.215***	0.999	-1.41**
(p-value)	0.000	0.274	0.034
F-Statistic (first Stage)	7.611	15.671	8.490
MSE-optimal bandwith $[-h, h']$	[-56, 274]	[-162, 342]	[-94, 328]
Observations	44	91	76
Order of polynomial	2	2	2
Treatment effect	-0.195***	0.737	-0.954**
(p-value)	0.000	0.340	0.042
F-Statistic (first Stage)	9.431	12.458	8.177
CER-optimal bandwith $[-h, h']$	[-45, 224]	[-132, 279]	[-77, 267]
Observations	44	91	76
Order of polynomial	2	2	2
Controls	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the average treatment effect at the threshold 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 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 per cent level, respectively. The controls includes the 4 quarters lagged values of credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank, the value of the O-SII buffer at inception and its expected values of the after 5 years after the notification and the set of banks' characteristic.

Table 5: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector (first quarter after first decision)

	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	-0.232	-0.052	0.336***
(p-value)	0.620	0.250	0.001
F-Statistic (first Stage)	7.055	10.281	6.238
MSE-optimal bandwith $[-h, h']$	[-151, 139]	[-71, 344]	[-120, 246]
Observations	71	57	67
Order of polynomial	2	2	2
Treatment effect	-0.195	-0.054	0.353***
(p-value)	0.475	0.118	0.000
F-Statistic (first Stage)	3.929	13.660	6.548
CER-optimal bandwith $[-h, h']$	[-123, 113]	[-58, 280]	[-98, 201]
Observations	71	57	67
Order of polynomial	2	2	2
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	0.023	0.079	0.124
(p-value)	0.471	0.197	0.346
F-Statistic (first Stage)	7.055	10.281	6.238
MSE-optimal bandwith $[-h, h']$	[-141, 1556]	[-89, 419]	[-158, 1664]
Observations	103	68	105
Order of polynomial	2	2	2
Treatment effect	0.006	0.017	0.138
(p-value)	0.738	0.529	0.215
F-Statistic (first Stage)	3.929	13.660	6.548
CER-optimal bandwith $[-h, h']$	[-115, 1268]	[-73, 342]	[-129, 1356]
Observations	103	68	105
Order of polynomial	2	2	2
Controls	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the average treatment effect at the threshold of O-SII identification on risk-taking. The dependent variable is the yearly change in the average risk-weights. We perform local 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 per cent level, respectively. The controls includes the 4 quarters lagged values of credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank, the value of the O-SII buffer at inception and its expected values of the after 5 years after the notification and the set of banks' characteristic.

cycle allows us to better control for observed and unobserved time-varying heterogeneity at the country level.

Tables 4 and 5 show the results and there is no significant change compared to the initial specification.[45]

A further concern we try and address stems from the delay in implementing capital surcharges; such phase-in delays could have reduced the short-term effects of the O-SII buffer tightening. Indeed, the implementation timing of the policy has been heterogeneous, and some countries postponed the full implementation of a non-zero capital buffer beyond the end of our sampling period. In addition, the buffer requirement's phase-in was also delayed for allowing banks to adjust their balance sheets smoothly. In order to control for this effect, we re-estimate the model accounting for country and bank characteristics correlated with such delays. The results in the lower panel of Tables 5 and 4 also factor in how 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. Based on these results, 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.

Based on these results, we can assess what would have been the credit growth for households and the financial sector if the O-SII framework was not introduced. Considering those O-SII banks close to the threshold, we can estimate the counter-factual growth of credit if they were not identified as O-SII. In particular, at inception, the identification implied a reduction on average credit growth for households and financial sector. When evaluating the costs and benefits of implementing capital-based macroprudential policies this potentially sizeable reduction in credit supply might call for some supporting measure.

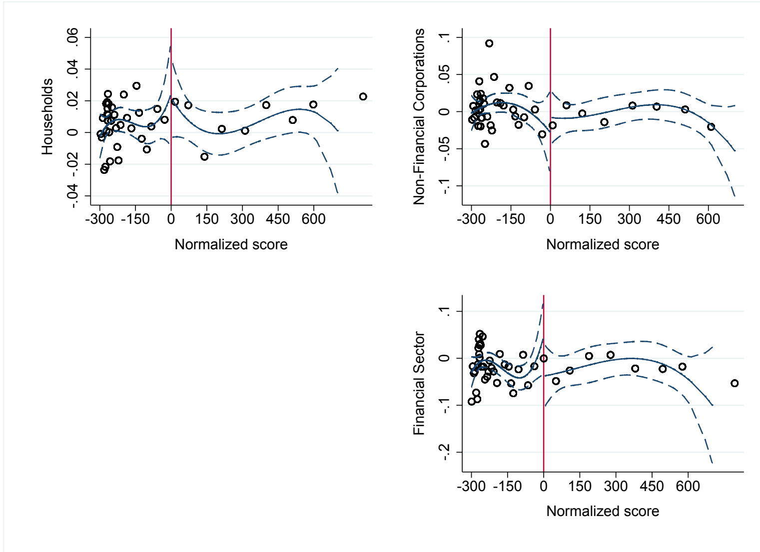
As a robustness check, we collect the information on the country of origin for exposures and risk-weighted exposures in order to consider those banks that have loans in countries different from their domicile (Table A5 and A6). To do so, we retrieve from supervisory data the geographical breakdown of the exposures at default (EAD) and risk-weighted assets for the different economic sectors (households, non-financial and financial corporations). Based on this information, we can compute the credit growth rate for each country and economic sector. We can, then, estimate the models adding time-country fixed effects. This last specification allows us to better control for credit demand factors. The results do not differ significantly from the one obtained in the baseline specification.

5.2 Evidence on the medium-term effects

Focusing on the first quarter after the decision and using 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.Instead, assessing the O-SII effect on a three-year horizon allows us to track banks' behaviour controlling for time-varying capital requirements and observable banks' characteristics. We start presenting graphically changes in the credit supply and banks' risk-taking identified as O-SII. Figures 4 and 5 show the unconditional quarterly change in credit and risk-weights' density of banks around the threshold, from the end of 2015 to the end of 2017. In particular, we show a scatter plot with each outcome variables' value against the normalized scores 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 identifying banks as O-SII on the volume of lending may be negligible (e.g. non-financial corporations). Nevertheless, it is possible to detect an adjustment when looking at our measures of risk-taking, in particular for the households sector.

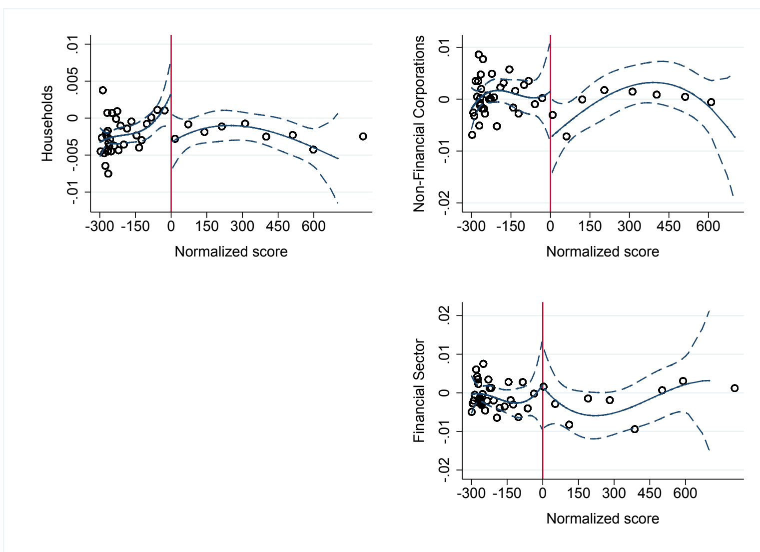
[45]We also estimate the model by restricting the countries where the designated O-SII buffer was strictly positive at inception.

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



Notes : The vertical axis displays the value of the credit growth for the relevant economic sector. 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 per cent confidence interval.

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



Notes : The vertical axis displays the risk-weights for the relevant economic sector. 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 per cent confidence interval.

The data used is at a 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. We propose two specifications to identify the medium-term effects on banks' risk-taking behaviour and credit supply. The upper panel presents the estimate for the impact of O-SII identification, controlling only for non-observable banks' characteristics and quarter fixed effects. The lower panel shows the estimates when we also include the lagged values of the yearly credit-to-GDP gap, the distance from the current and required CET1 ratio,[46] and the risk-weights density. Furthermore, we add in our specification explanatory variables related to the profile of current and future O-SII requirements (one month, one year, and five years ahead). Few banks were identified as O-SII in the subsequent assessments, while only two banks ceased to be O-SII after the first assessment. In these cases, only banks effectively identified as O-SII in each yearly O-SII assessment were considered as "treated" in the analysis.

Table 6 presents the results for credit supply, defined as the quarterly credit growth rate as the change in the log of a banks' credit volume. The estimates show 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 also hold when we include country- and bank-specific control variables to address correlation concerns between the differences in banks' characteristics and 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 we account for observable and non-observable characteristics of banks, countries and time fixed effects, banks identified as O-SII reduce their risk-taking by two to four percentage points in the households and financial sectors, compared to those just below the threshold.[47] Based on this evidence, the costs related to introducing the O-SIIs framework were quite limited, as credit supply reduction was limited, while the benefits in terms of reduction of risk-taking were still significant. This evidence sheds new light on the role of macroprudential policies and calls for further assessment of the cost and benefits of changes in capital requirements.

In terms of real effects, we find that banks constrained with an O-SII buffer shifted lending towards safer borrowing in the household and financial sector, therefore not affecting SME financing, which is under the corporates segment. In other words, we do not find evidence of a significant effect in the non-financial corporation sector, which includes SMEs. The risk shifting is compatible with the results shown by Degryse et al. (2021), where secure lending becomes more attractive because it requires less regulatory capital than unsecured lending.

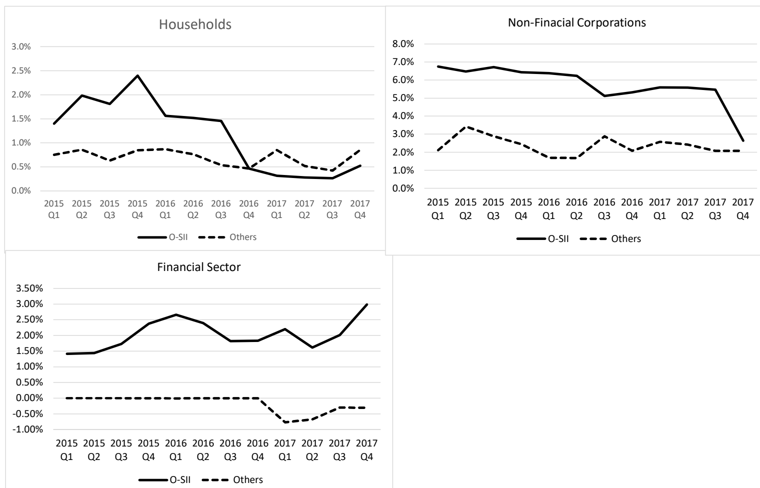
Our results show that banks adjusted the average risk-weights downwards within the household and financial sectors. I.e., the risk of retail obligors decreased, which can be explained by a better risk management (or risk optimisation), such as i) lower loan-to-value given the real estate developments or the amortisation of the loans, ii) further consideration of eligible collateral, and iii) improved creditworthiness of the counterparts under the upturn macroeconomic development (i.e. better credit quality of the new loans). As mentioned above, we can explain the banks' re-balancing behaviour for lending and risk-taking in the households and financial institutions sectors by the banks willingness to defend profitability, which is crucial in EU banking system under the low interest rate environment. This environment also improves the creditworthiness of the obligors under the upturn macroeconomic during the horizon of our study.Indeed, Altavilla et al. (2018) show that the protracted period of low monetary rates hurt profits. However, this damage only materialised after a long time period and was counterbalanced by improved macroeconomic

[46] 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.

[47] 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 on 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.

conditions. Provisions and risk also decreased, therefore compensating the unintended impacts on profits. In other words, banks decreased their risk position towards safer options in the households and financial sector, allowing for compliance with the capital buffer requirement while avoiding a strong reduction in profitability. Degryse et al. (2021) document an increase in collateralization for loans to firms. Yet, Figure 6 shows that the reduction in risk weighted exposure may not be driven by an increase in the collateral backing loans.[48] Over time, the median value of collateral as a percentage of the underlying exposure did not increase for banks O-SII banks. Therefore the reduction highlighted in the medium-term perspective may reflect the change in lending standards and in the risk assessment of banks.

Figure 6: Value of the collateral over the value of the exposure (end-2015 - end-2017)



Notes : The vertical axis displays the value of the collateral as percentage points of the underlying value of the loan. For the two groups the median value is shown. Only banks with score within 200 bps are shown in order to be comparable with estimate results.

[48] Following the EU legislation (CRR), and based on the credit risk standardised approach, the risk-weight for retail portfolios is 75 %. However, exposures that are secured by residential properties are assigned to a risk-weight of 35%. This suggests that banks to lower down the risk-weights would need to increase the share of collateralised loans, which follows the EU legislation and the respective eligible credit risk mitigation

Table 6: Credit Supply: Average effect of O-SII identification by economic sector (medium-term)

	Households	Non-financial corporations	Financial sector
Δ*Log Credit*			
Treatment effect	-0.005	0.017	0.01
(p-value)	0.359	0.128	0.724
MSE-optimal bandwith $[-h, h']$	[-143, 1285]	[-114, 1185]	[-151, 2326]
Observations	145	116	153
Order of polynomial	2	2	2
Treatment effect	-0.007	0.016	0.014
(p-value)	0.219	0.175	0.699
CER-optimal bandwith $[-h, h']$	[-116, 1044]	[-93, 963]	[-122, 1890]
Observations	1040	938	1398
Order of polynomial	2	2	2
Bank fixed effect	Y	Y	Y
Quarter fixed effect	Y	Y	Y
Controls	None	None	None

	Households	Non-financial corporations	Financial sector
Δ*Log Credit*			
Treatment effect	-0.005	0.038	-0.044
(p-value)	0.588	0.214	0.660
MSE-optimal bandwith $[-h, h']$	[-65, 695]	[-130, 1180]	[-89, 1336]
Observations	402	654	603
Order of polynomial	2	2	2
First-stage F-statistic			
Treatment effect	-0.014	0.043	-0.022
(p-value)	0.226	0.201	0.798
CER-optimal bandwith $[-h, h']$	[-53, 565]	[-105, 958]	[-72, 1085]
Observations	341	549	506
Order of polynomial	2	2	2
Bank fixed effect	Y	Y	Y
Quarter fixed effect	Y	Y	Y
Controls	Country and bank controls	Country and bank controls	Country and bank controls

Notes : Estimates for the average treatment effect at the threshold 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 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 per cent level, respectively.

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

	Households	Non-financial corporations	Financial sector
Δ*Risk-weight*			
Treatment effect	-0.009***	0.004	0.006
(p-value)	0.005	0.443	0.373
MSE-optimal bandwith $[-h, h']$	[-171, 345]	[-273, 1585]	[-148, 928]
Observations	1007	3022	1229
Order of polynomial	2	2	2
Treatment effect	-0.01***	0.005	0.005
(p-value)	0.001	0.396	0.511
CER-optimal bandwith $[-h, h']$	[-143, 288]	[-222, 1287]	[-120, 754]
Observations	846	1740	983
Order of polynomial	2	2	2
Bank fixed effect	Y	Y	Y
Quarter fixed effect	Y	Y	Y
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ*Risk-weight*			
Treatment effect	-0.029***	0.031	-0.042**
(p-value)	0.009	0.174	0.014
MSE-optimal bandwith $[-h, h']$	[-115, 418]	[-107, 1037]	[-161, 1264]
Observations	410	565	739
Order of polynomial	2	2	2
Treatment effect	-0.025**	0.035	-0.049**
(p-value)	0.011	0.196	0.011
CER-optimal bandwith $[-h, h']$	[-96, 348]	[-87, 843]	[-131, 1027]
Observations	348	495	620
Order of polynomial	2	2	2
Bank fixed effect	Y	Y	Y
Quarter fixed effect	Y	Y	Y
Controls	Country and bank controls	Country and bank controls	Country and bank controls

Notes : Estimates for the average treatment effect at the threshold of O-SII identification on risk-taking. The dependent variable is the quarterly change in the average risk-weight density. We perform a local 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 per cent level, respectively.

6 Conclusions

In this paper, we exploit the provision of the EU framework[49] 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 randomised experiment. 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 insignificant.[50] Results suggest that banks constrained by higher capital buffers, shifted, in the medium-term, their lending to less risky 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 their risk-weighted assets (the denominator of the capital ratio).[51] Such finding contributes to 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 to be raised instead of the capital ratio could mitigate the optimisation of risk-weighted assets; indeed, such solution has been applied in the U.S. stress test conducted in 2009 (Hirtle et al. (2009)).

Despite affecting risk-taking and following the conclusions of Buch and Prieto (2014), the analysed policy change seems 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 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. Our findings support the discussion on the 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)[52] and Repullo (2003),[53] our results show that capital requirements that 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.

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

[50] 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.

[51] 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)).

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

[53] Capital requirements can reduce banks gambling incentives, leading to a prudent equilibrium.

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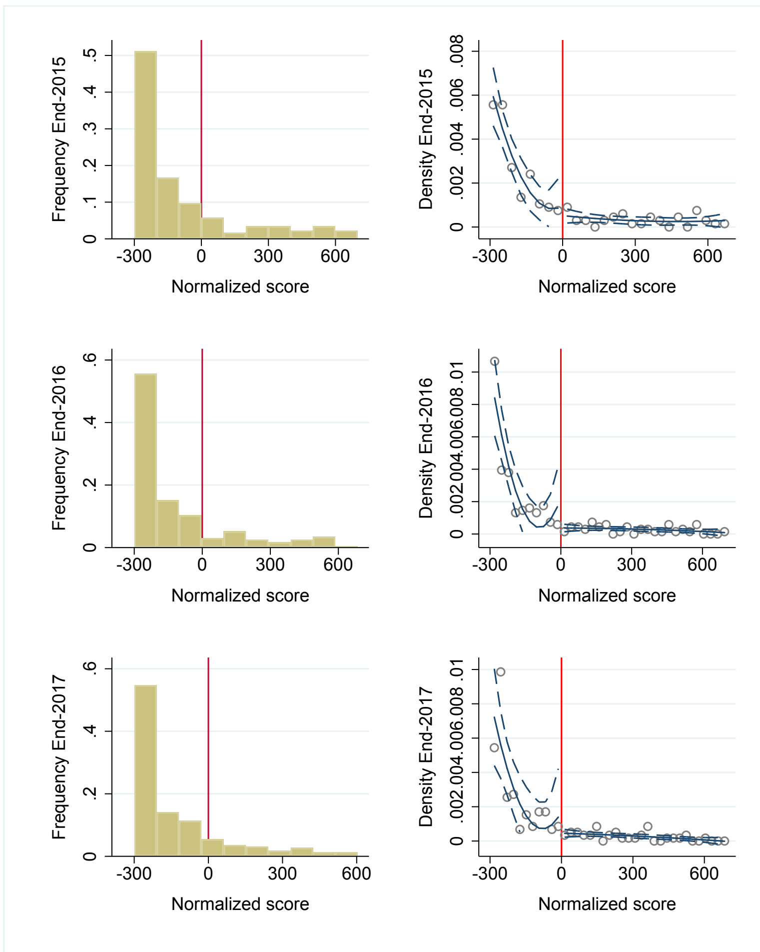
Appendix A.

Table A1: Additional descriptive statistics

		Not O-SII	O-SII
		Post-notification	Post-notification
		∆ Log Credit (quarterly)	
Households	*Min*	-8.67	-3.27
	p10	-0.04	-0.03
	p90	0.05	0.04
	Max	6.44	3.94
Non-financialcorporations	*Min*	-14.45	-2.57
	p10	-0.11	-0.06
	p90	0.12	0.06
	Max	9.32	1.09
Financial sector	*Min*	-14.36	-2.31
	p10	-0.31	-0.23
	p90	0.32	0.18
	Max	11.32	2.29
		∆ Risk Weights	
Households	*Min*	-0.84	-2.43
	p10	-0.01	-0.01
	p90	0.01	0.01
	Max	0.87	1.47
Non-financialcorporations	*Min*	-4.45	-1.18
	p10	-0.03	-0.02
	p90	0.03	0.02
	Max	5.10	0.70
Financial sector	*Min*	-1.64	-0.54
	p10	-0.03	-0.04
	p90	0.02	0.03
	Max	0.99	0.54

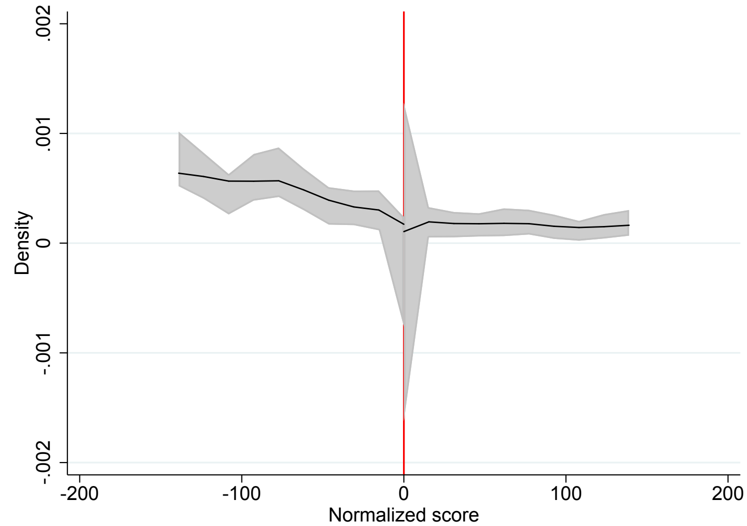
Notes: Data between 2014:Q4 and 2017:Q4. Mean values are computed separately for banks below and above the threshold, as well as before and after the notification of the O-SII assessment. Standard deviations are reported in parenthesis. The credit growth rate is the change in the log of a banks' credit volume. The quarterly changes are in percentage points.

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



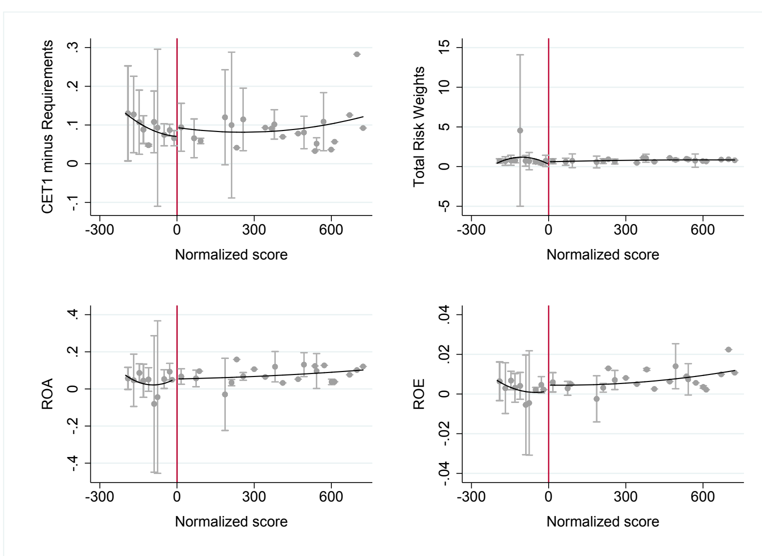
Notes: The graphs on the left-hand side exhibit the frequency of normalized scores, while the graphs on the right-hand side represent the McCrary test of density continuity for each of the yearly O-SII reviews. A weighted kernel estimation is performed separately on each side of the cutoff.

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 equal 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 (dates of decisions)

	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 associated estimates. The results are robust if we use the optimal bandwidth in the equation used for testing the continuity of the covariates.

Table A3: Credit Growth: Average effect of O-SII identification by economic sector (first quarter after the notification)

	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.341***	0.758	-1.109***
(p-value)	0.000	0.895	0.000
MSE-optimal bandwith $[-h, h']$	[-474, 474]	[-593, 593]	[-592, 592]
Observations	6743	6181	5226
Order of polynomial	1	1	1
Treatment effect	-0.443***	0.796	-1.11***
(p-value)	0.000	0.985	0.000
CER-optimal bandwith $[-h, h']$	[-278, 278]	[-351, 351]	[-355, 355]
Observations	4370	5810	4982
Order of polynomial	1	1	1
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.139***	4.661	-0.336***
(p-value)	0.000	0.349	0.000
MSE-optimal bandwith $[-h, h']$	[-369, 2665]	[-369, 1985]	[-369, 2426]
Observations	371	371	371
Order of polynomial	1	1	1
Treatment effect	-0.002***	0.386	-0.663***
(p-value)	0.000	0.279	0.000
CER-optimal bandwith $[-h, h']$	[-217, 1567]	[-219, 1177]	[-222, 1458]
Observations	5456	3627	3366
Order of polynomial	1	1	1
Controls	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the average treatment effect at the threshold 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 per cent level, respectively. The controls includes the 4 quarters lagged values of credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank, the banks' total exposure , the value of the O-SII buffer at inception and its expected values of the after 5 years after the notification.

Table A4: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector (first quarter after the notification)

	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	-0.041	0.036	0.327***
(p-value)	0.170	0.493	0.001
F-Statistic (first Stage)	4.782	7.201	6.267
MSE-optimal bandwith $[-h, h']$	[-90, 159]	[-58, 314]	[-79, 194]
Observations	56	58	54
Order of polynomial	1	1	1
Treatment effect	-0.044	-0.014	0.33***
(p-value)	0.148	0.804	0.000
F-Statistic (first Stage)	4.528	7.424	6.711
CER-optimal bandwith $[-h, h']$	[-75, 133]	[-49, 262]	[-66, 162]
Observations	56	58	54
Order of polynomial	1	1	1
Controls	None	None	None

	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	0.004	0.096	0.103
(p-value)	1.000	0.098	0.285
F-Statistic (first Stage)	4.782	7.201	6.267
MSE-optimal bandwith $[-h, h']$	[-89, 784]	[-67, 257]	[-128, 980]
Observations	65	45	103
Order of polynomial	1	1	1
Treatment effect	-0.007	0.092	0.109
(p-value)	0.668	0.070	0.271
F-Statistic (first Stage)	4.528	7.424	6.711
CER-optimal bandwith $[-h, h']$	[-74, 656]	[-56, 215]	[-107, 820]
Observations	65	45	103
Order of polynomial	1	1	1
Controls	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the average treatment effect at the threshold 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 per cent level, respectively. The controls includes the 4 quarters lagged values of credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank, the banks' total exposure , the value of the O-SII buffer at inception and its expected values of the after 5 years after the notification.

Table A5: Credit Growth: Average effect of O-SII identification by economic sector and country of domicile of the borrower (first quarter after first decision)

	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.341***	0.758	-1.109***
(p-value)	0.000	0.895	0.000
MSE-optimal bandwith $[-h, h']$	[-474, 474]	[-593, 593]	[-592, 592]
Observations	6743	6181	5226
Order of polynomial	2	2	2
Treatment effect	-0.443***	0.796	-1.11***
(p-value)	0.000	0.985	0.000
CER-optimal bandwith $[-h, h']$	[-278, 278]	[-351, 351]	[-355, 355]
Observations	4370	5810	4982
Order of polynomial	2	2	2
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.148***	1.73	-3.401***
(p-value)	0.000	0.349	0.000
MSE-optimal bandwith $[-h, h']$	[-369, 1553]	[-369, 930]	[-369, 1682]
Observations	371	371	371
Order of polynomial	2	2	2
Treatment effect	-0.215***	-1.756	-0.015***
(p-value)	0.000	0.279	0.000
CER-optimal bandwith $[-h, h']$	[-217, 913]	[-219, 552]	[-222, 1011]
Observations	3929	2977	2798
Order of polynomial	2	2	2
Controls	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the average treatment effect at the threshold 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 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 per cent level, respectively. The controls includes the 4 quarters lagged values of credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank, the value of the O-SII buffer at inception and its expected values of the after 5 years after the notification and the set of banks' characteristics. Fixed effects for banks and country of domicile of the borrower are included. From supervisory data, for example, we can have information on the value of loans of each bank to each country of destination e.g. France, Italy, Germany. Therefore we have countries whose borrowers can have loans from multiple banks also from foreign countries and we can identify non-observable and time-invariant country specific effect.

Table A6: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector and country of domicile of the borrower (first quarter after first decision)

	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	-0.621***	0.811	-1.141***
(p-value)	0.000	0.463	0.000
MSE-optimal bandwith $[-h, h']$	[-489, 489]	[-593, 593]	[-456, 456]
Observations	6415	5919	4397
Order of polynomial	2	2	2
Treatment effect	-0.698***	0.861	-1.037***
(p-value)	0.000	0.335	0.000
CER-optimal bandwith $[-h, h']$	[-288, 288]	[-352, 352]	[-275, 275]
Observations	4170	5578	2648
Order of polynomial	2	2	2
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	-0.326***	2.889***	0.445
(p-value)	0.000	0.000	0.348
MSE-optimal bandwith $[-h, h']$	[-369, 2600]	[-610, 610]	[-369, 1147]
Observations	371	612	371
Order of polynomial	2	2	2
Treatment effect	-0.104***	2.76***	0.313
(p-value)	0.000	0.000	0.173
CER-optimal bandwith $[-h, h']$	[-217, 1533]	[-363, 363]	[-223, 695]
Observations	5261	5380	2432
Order of polynomial	2	2	2
Controls	Country and bank specific	Country and bank specific	Country and bank specific

Notes : Estimates for the average treatment effect at the threshold of O-SII identification on risk-taking. The dependent variable is the yearly change in the average risk-weights. We perform local 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 per cent level, respectively. The controls includes the 4 quarters lagged values of credit-to-GDP gap for each country, the distance from the actual and the required CET1 ratio for each bank, the value of the O-SII buffer at inception and its expected values of the after 5 years after the notification and a set of banks' characteristics. Fixed effects for banks and country of domicile of the borrower are included. From supervisory data, for example, we can have information on the value of loans of each bank to each country of destination e.g. France, Italy, Germany. Therefore we have countries whose borrowers can have loans from multiple banks also from foreign countries and we can identify non-observable and time-invariant country specific effect.

Table A7: Credit supply: Average effect of O-SII identification by economic sector for different bandwidths (first quarter after first decision)

Household		Left Bandwidth				
		50	100	150	200	250
Right Bandwidth	50	-0.73	-1.007 ***	-1.239 ***	-1.078 ***	-0.725 ***
	100	-0.224 ***	-0.742 *	-1.419	-1.596	-0.148 ***
	150	-0.217 **	-0.625 **	-0.977	-0.988 *	0.263 **
	200	-0.209 ***	-0.399 **	-0.447 *	-0.439 *	0.147 *
	250	-0.212 ***	-0.35	-0.377	-0.38	0.156 **
Non-financial corporations		**Left Bandwidth**				
		50	100	150	200	250
Right Bandwidth	50	0.43 ***	0.777	1.308 ***	1.122 **	1.163 *
	100	0.544	0.974	2.616	2.932	3.706
	150	0.382	0.799	2.121	2.126	2.296
	200	0.275	0.54	1.019	0.936	0.873
	250	0.323	0.56	0.987	0.951	0.895
Financial sector		**Left Bandwidth**				
		50	100	150	200	250
Right Bandwidth	150	-1.015	-2.022	-2.73	-3.688	-3.5
	200	-0.954	-1.424	-1.524	-1.778 *	-1.374 ***
	250	-0.87 *	-1.251 *	-1.291 *	-1.491 **	-1.119 ***
	300	-0.935	-1.388	-1.452	-1.583	-1.164 *
	350	-0.964	-1.456	-1.529	-1.63	-1.19

Notes : Estimates for the effect of O-SII identification on credit supply for different bandwidths. Each column corresponds to a different value of the left bandwidth, ranging from a normalized score of -50 to a score of -250. Each row corresponds to a different value of the right bandwidth. For each sector we use a different range of values. This ensures that for each sector the optimal bandwidth falls within the range considered. 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 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 per cent level, respectively.

Table A8: Risk-taking (risk-weights): Average effect of O-SII identification by economic sector for different bandwidths (first quarter after first decision)

Household		Left Bandwidth				
		50	100	150	200	250
Right Bandwidth	1400	-0.01	-0.01	0	-0.01	-0.005
	1450	-0.009	-0.009	0.001	-0.008	-0.003
	1500	-0.009	-0.008	0.002	-0.007	-0.002
	1550	-0.008	-0.007	0.002	-0.006	-0.002
	1600	-0.008	-0.007	0.003	-0.006	-0.001
Non-financial corporations		**Left Bandwidth**				
		50	100	150	200	250
Right Bandwidth	200	-0.041	-0.115	-0.185	-0.225	-0.222
	300	-0.037	-0.081	-0.141	-0.19	-0.194
	400	-0.016	0.001	-0.052	-0.116	-0.131
	500	-0.008	0.03	-0.023	-0.09	-0.108
	550	-0.009	0.035	-0.021	-0.091	-0.111
Financial sector		**Left Bandwidth**				
		50	100	150	200	250
Right Bandwidth	1300	0.274 ***	0.267 ***	0.321 *	0.268	0.163
	1400	0.268 ***	0.259 ***	0.308 *	0.254	0.155
	1500	0.263 ***	0.252 ***	0.293 *	0.241	0.145
	1600	0.259 ***	0.248 ***	0.285 *	0.232	0.14
	1700	0.254 ***	0.241 ***	0.271 **	0.218 *	0.131

Notes : Estimates for the average treatment effect at the threshold of O-SII identification on risk-taking for different bandwidths. Each column corresponds to a different value of the left bandwidth, ranging from a normalized score of -50 to a score of -250. Each row corresponds to a different value of the right bandwidth. For each sector we use a different range of values. This ensures that for each sector the optimal bandwidth falls within the range considered. The dependent variable is the quarterly change in the average risk-weight density. We perform a local 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 per cent level, respectively.

Table A9: Credit supply: Average effect of O-SII identification by economic sector for different bandwidths (medium-term)

	Household	Left Bandwidth				
		-50	-100	-150	-200	-250
Right Bandwidth	1000	-0.002	0.001	-0.002	-0.009	-0.002
	1500	0.000	-0.011	-0.053	-0.081	-0.023
	2000	-0.010	0.014	-0.016	-0.013	-0.004
	2500	-0.023	-0.031	0.023	0.014	0.004
	Non-financial corporations	**Left Bandwidth**				
		50	100	150	200	250
Right Bandwidth	1000	0.009	0.021	0.019	0.034	0.031 *
	1500	0.020	0.013	0.018 *	0.026	-0.005
	2000	0.030	0.046 *	0.026	0.034	-0.009
	2500	0.003	0.006	0.014	0.024	-0.015
	Financial sector	**Left Bandwidth**				
		50	100	150	200	250
Right Bandwidth	1000	-0.05	0.04	-0.04	-0.01	-0.02
	1500	-0.02	-0.03	-0.05	-0.04	-0.04 *
	2000	-0.01	-0.02	-0.01	-0.04	-0.03
	2500	-0.02	-0.03	0.00	0.01	0.00

Notes : Estimates of the average treatment effect at the threshold of O-SII identification on credit supply for different bandwidths. Each column corresponds to a different value of the left bandwidth. Each row corresponds to a different value of the right bandwidth. For each sector we use a different range of values. This ensures that for each sector the optimal bandwidth falls within the range considered. 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). 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 fixed effect for bank and time. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A10: Risk-taking (risk-weights): Average effect of O-SII identification by economic sector for different bandwidths (first quarter after first decision)

Household		Left Bandwidth				
		-100	-150	-200	-250	-300
Right Bandwidth	300	-0.017 **	-0.019 ***	-0.022 **	-0.010	-0.003
	400	-0.023 ***	-0.026 ***	-0.025***	-0.016 ‘*	-0.003
	500	-0.012 **	-0.018 **	-0.026 *	-0.018 *	-0.011
	600	-0.011 **	-0.007	0.028 **	-0.016 **	-0.014

Non-financial corporations		Left Bandwidth				
		50	100	150	200	250
Right Bandwidth	900	0.014	0.015	-0.018	-0.025	-0.012
	1000	0.037	0.041	0.044	0.034	0.033
	1100	-0.016	0.010	0.058	0.103	0.140
	1200	0.080	-0.038	-0.073	-0.021	0.098

Financial sector		Left Bandwidth				
		50	100	150	200	250
Right Bandwidth	1000	-0.031	-0.050 ***	-0.043 *	-0.070 *	0.022
	1100	-0.034 *	-0.035 **	-0.037 **	-0.04 **	-0.03 **
	1200	-0.045 *	-0.042 *	-0.052 *	-0.058 *	0.031
	1300	-0.048 **	-0.03 *	-0.033 *	-0.29	0.108

Notes : Estimates for the average treatment effect at the threshold of O-SII identification on risk-taking for different bandwidths. Each column corresponds to a different value of the left bandwidth. Each row corresponds to a different value of the right bandwidth. For each sector we use a different range of values. This ensures that for each sector the optimal bandwidth falls within the range considered. The dependent variable is the quarterly change in the average risk-weight density. We perform a local 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 included. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.