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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January 2, 2024

Abstract

We study the impact of higher capital buffers on bank lending and risk-taking behaviour, at different time horizons following the initial policy decision. Employing a regression discontinuity design and confidential centralised supervisory data for euro area banks from 2014 to 2017, our research uniquely explores the effects of the EU policy on other systemically important institutions (O-SIIs) through a quasi-randomised experiment, exploiting the induced policy change and discontinuity of the O-SII identification process. Our findings show that the introduction of the O-SII buffers resulted in a short-term reduction in credit supply to households and financial sector, followed by a medium-term shift towards less risky borrowers, particularly in the household sector. We find a temporary cut in loan growth post-capital hikes, succeeded by a rebound in the medium-term. Our results substantiate the hypothesis that higher capital buffers can positively discipline banks by reducing risk-taking in the medium-term. At the same time, evidence suggests a limited adverse impact on the real economy, characterised by a temporary reduction in credit supply restricted to instances of macroprudential policy tightening.

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

*We would like to thank the Editorial Board of the ECB Working Paper Series, Carmelo Salleo, Steven Ongena, Paolo Emilio Mistrulli, Matias Cattaneo, Alessio Reghezza and the participants of the ECB internal seminar for their useful comments and suggestions. Special thanks to Zymantas Budrys and Jonas Peeters who contributed to the earliest drafts of the paper. The opinions in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank or the Eurosystem.

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1 Introduction

In the context of the banking sector, a key instrument in macroprudential policy is the implementation of capital buffer requirements. Focusing on capital buffers, Europe employs the combined buffer requirements, an additional layer on top of minimum capital requirements. This includes the capital conservation buffer, systemic risk buffer, buffers for globally and other systemically important institutions, and the countercyclical capital buffer. The fundamental aim of macroprudential policy is to prompt banks to absorb losses while maintaining lending to the real economy during periods of stress, thus contributing to the smoothing of financial cycles. The literature on the effectiveness of macroprudential instruments has rapidly expanded, with initial findings that indicate short-term impacts of policy decisions. However, these insights offer limited guidance for policy measures aiming to shape the banking system in the medium- and long-term, primarily due to the relatively limited experience in implementing macroprudential measures. Some measures - widely considered macroprudential - were taken already in the 1930s and 1950s to support domestic financial systems and influence credit supply (Haldane, 2011).[1] Traditionally, a combination of monetary, fiscal, and prudential policies was deemed adequate for ensuring macroeconomic and financial stability. Yet, the aftermath of the financial crisis prompted a reconsideration of this consensus. It became evident that developments in the financial system bear significance for macroeconomic stability, even in periods of low and stable inflation with seemingly robust fiscal positions. However, a key challenge arises in conducting a comprehensive assessment of a macroprudential stance (Stein, 2014; Galati and Moessner, 2013; Woodford, 2012; Taylor, 2009). Such assessment requires an understanding of the effectiveness of each instrument in mitigating systemic risk and the intricate interactions between policy instruments (e.g., macroeconomic and macroprudential ones). Despite many challenges, increasing efforts have been made in recent years to bridge these gaps. In 2011, the International Monetary Fund (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 have further enriched this survey.[2]

In recent literature exploring the nexus between capital regulation and economic growth, various datasets have been compiled to advance understanding.[3] The focus in existing literature has centered on buffer requirements and their impact on bank capital and credit supply, with potential repercussions for the real economy. This paper deviates from existing literature by providing a causal assessment of the effectiveness of higher capital requirements. Our study exploits the institutional setting used for applying additional capital surcharges to other systemically important institutions (O-SII) within the euro area countries, under the European Central Bank (ECB) Single Supervisory Mechanism (SSM).[4] This paper, uniquely, delves into the cross-section impacts and the medium-term consequences of newly introduced macroprudential policies.

Since 2015, more than 110 banks have been designated as O-SII, subject to additional Common Equity Tier 1 (CET1) capital requirements. Financial institutions, deemed systemically important, pose risks of moral hazard and misaligned incentives (ESRB, 2015). Shocks to these systemically important institutions can propagate losses and liquidity shortages throughout the financial system. Despite variations in policy implementation and phase-in arrangements across countries, the identification of O-SII generally adhered to

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

[2] Using this survey, Lim et al. (2013) constructed a macroprudential index, while Cerutti et al. (2017a, 2017b, 2017c) provide a valuable insights on how countries use prudential instruments.

[3] Noteworthy contributions include databases on housing market policy actions (Shim et al., 2013), macroprudential measures related to house prices in Central, Eastern, and South-Eastern Europe (Vandenbussche et al., 2012), legal reserve requirements for industrial and developing countries (Federico et al., 2012a), changes in prudential tool usage (Cerutti et al., 2017c), macroprudential policies in the EU banking sectors (Budnik and Kleibl, 2018).

[4] At the first introduction of the policy and subsequent years.

the European Banking Authority guidelines (EBA, 2014).[5] The distinctive features of the O-SII framework provides us with an ideal setup for causally assess the impact of higher capital requirements on banks' lending and risk-taking behaviour of banks in close proximity to the threshold. By exploiting the policy change and the induced discontinuity in the O-SII identification process, our design assumes a probabilistic assignment around the threshold, at different time horizons relative to the initial policy decision, creating a quasi-randomised experiment. We employ a regression discontinuity design (Cattaneo, Idrobo and Titiunik, 2017a, 2017b) to assess the impact of the O-SII capital regulation on the behaviour of banks with scores around the threshold. In particular, we build on the fuzzy regression discontinuity design that accommodates the probabilistic nature of treatment assignment, aligning with the framework for the O-SII identification.

This research contributes uniquely to the existing literature by leveraging in the EU policy for systemically important institutions, offering valuable insights into the longstanding debate on the effects of bank capital regulation on credit supply and risk-taking. Our paper falls within two key strands of literature. First, it contributes to the empirical literature studying the effect of capital regulation on credit supply.[6] Second, our paper delves into the literature on the effect of policy actions on banks' risk-taking channel.[7] Leveraging on confidential centralised supervisory data, this paper offers a direct insight into the lending and risk-taking dynamics exhibited by all euro area banks.

In line with previous evidence in the literature,[8] we find that euro area banks designated as O-SII exhibited a short-term reduction in lending to households and financial sector. In the short-term, a yearly increase of approximately 0.5 percent in capital buffers (for banks closer to the threshold) is associated with a decline in lending of around 0.2 percentage points for households and 1.3 percentage points for the financial sector (if the increase in capital buffers is 1 percent, the corresponding decline in lending for households is around 0.4 percentage points). This follows noteworthy studies, such as De Jonghe et al. (2020), Berrospide and Edge (2019), Gropp et al. (2018), Fraisse et al. (2017), Mésonnier and Monks (2015), Aiyar et al. (2014, 2016), Bridges et al. (2014), and Hanson et al. (2011) that consistently find banks cut lending to comply with higher capital requirements. Additionally, our study does not uncover substantial evidence of the policy significantly impacting corporate lending, a result robust to both time-horizon (short- or medium-term) and adjustment type (credit volume or risk-weights). The divergence in findings may be attributed to higher bank lending rates for corporates compared to households, making the corporate segment relatively more profitable. The absence of a significant effect on corporate lending may therefore reflect banks' endeavours to maintain sufficiently high returns, a strategic response to the prolonged weak profitability observed in the European banking industry since mid-2012 until 2021. Our results align with concerns about a policy-induced credit crunch as indicated by Acharya et al. (2011). Similar to us, Buch and Prieto (2014) and Bridges et al. (2014) show a temporary cut on loan growth post-capital requirement hikes, yet loan growth

[5] According to these guidelines, each bank receives a score based on four mandatory indicators that serve as proxy for systemic importance. Banks exceeding a country-specific threshold based on this score are automatically designated as O-SII. National authorities maintain some discretion in O-SII identification, potentially leading to cases where banks with scores below the threshold are identified as O-SII.

[6] As noted by Gropp et al. (2018), banks can increase their capital ratios by increasing equity (numerator of the capital ratio) or reducing risk-weighted assets (denominator of the capital ratio). This study focuses on the denominator of the capital ratio to evaluate banks' lending behaviour.

[7] The theoretical research on the risk-taking channel has been increasing significantly during the last few years Borio and Zhu (2012), Dell'Ariccia et al.(2014, 2017) and Adrian and Shin (2008, 2009, 2010a and 2010b).

[8] Admati et al. (2018) suggest that banks' shareholders prefer to increase their capital ratios by reducing risk-weighted assets instead of raising new capital. Peek and Rosengren (1997) find that binding risk-based requirements caused Japanese banks to decrease lending in the United States. Noss and Toffano (2014) show a 15 basis points increase in UK banks' capital ratio leads to a 1.4 per cent reduction in lending after 16 quarters. Becker and Ivashina (2014) find loan substitution during tight lending standards and depressed aggregate lending. Martynova (2015) suggests that banks facing higher capital requirements can reduce both credit supply and demand by raising lending rates.

mostly recovers in the medium and long-term. These findings, in line with Furlong and Keeley (1989) and Jiménez et al. (2015, 2017) suggest that increased capital leads to a non-significant impact on credit growth for banks near the threshold in the medium run or to smoothing of the credit supply cycles.

Our findings also support the hypothesis that moral hazard costs, contributing to excessive risk-taking (Rochet, 1992), are mitigated by the introduction of the O-SII surcharge as risk-weights decrease in the medium-term in the household sector, indicating a positive disciplining effect.[9] This result is corroborated by Konietschke et al. (2022), finding that banks subject to stress test-related capital requirements tend to shift credit away from riskier borrowers toward safer ones in the household sector, enhancing overall safety while sacrificing profitability in this portfolio.[10] Also, Altunbas et al. (2018) shows that macroprudential tools impact banks' risk-taking significantly. Furthermore, Degryse et al. (2021) study the impact of the 2011 EBA capital exercise on Portuguese banks, focusing on increased collateralisation for corporate loans. Our analysis extends to various sectors and encompasses the entirety of the euro area banking system, uncovering a mechanism akin to that observed by Degryse et al. (2021) affecting the household sector, where O-SII banks notably adjust their risk profile. From a close inspect on the data, our medium-term results for the reduction in risk-taking seems to be explained by alterations in lending standards and banks' risk assessment or managing practices, rather than an actual increase in the level of collateralisation.

In summary, our study suggests that the introduction of the O-SII framework incurred limited costs, efficiently managing the reduction in credit supply while yielding risk reduction benefits. Notably, O-SII-designated banks exhibited a short-term reduction in credit supply to households and financial sector, coupled with a strategic shift in the medium-term towards less risky borrowers, particularly within the household sector. This risk-taking adjustment can be attributed to improved risk management practices, including lower loan-to-value ratios, enhanced consideration of eligible collateral, and improved creditworthiness due to favourable macroeconomic conditions. In essence, banks strategically decreased their lending (short-term) and risk position (medium-term) towards safer options in the households, enabling compliance with the capital buffer requirement while avoiding a substantial reduction in profitability, especially considering higher lending rates in the corporates segment.

The remainder of the paper is organised 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 validity of our empirical strategy. Section 5 presents the results and provides several robustness checks. Section 6 concludes.

2 The O-SII Identification Framework

The macroprudential framework[11] for addressing structural risks includes three types of buffers: global systemically institutions (G-SII) buffer, O-SII buffer, and systemic risk buffer (SyRB). The purpose of the G-SII and O-SII buffers is to mitigate the risk of large, interconnected banks relying on government support during times of crisis. G-SIIs are identified by the Financial Stability Board (FSB) based on their size, interconnectedness, and complexity, while O-SIIs are identified by national authorities based on their

[9]The additional O-SII buffer aims to enhance banks' capitalization, promoting financial stability by reducing risk-taking incentives and increasing resilience against potential losses.

[10]This effect is pronounced for banks in the Supervisory Review and Evaluation Process with undisclosed stress tests and voluntary non-disclosure of Pillar 2 Requirements.

[11]For in-depth information on the methodology for identifying and defining subcategories of G-SIIs, as well as disclosure guidelines, it is recommended to consult the EBA Regulatory Technical Standards and Guidelines on disclosure of G-SIIs, Directive 2013/36/EU (CRD IV), and the framework established by the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS).

impact on the domestic financial system and the real economy. The required amount of capital buffer varies depending on the systemic risk of the bank, where higher requirements are allocated to more systemically important institutions. Institutions identified as systemically important both nationally and globally must apply the higher of the G-SII and O-SII buffers.[12] The SyRB amount is defined at national level and aims to address systemic risks that are not covered by the Capital Requirements Regulation (CRR) or by the countercyclical capital buffer (CCyB) or the G-SII/O-SII buffers.[13] These buffers are crucial in reducing the moral hazard associated with too-big-to-fail banks, as they ensure that banks are more resilient and less likely to require public support during times of financial stress.[14]

In particular, the O-SII framework is defined in Article 131(3) of the Directive 2013/36/EU (CRD IV) and the EBA Guidelines (EBA/GL/2014/10). It established a two-step procedure for identifying O-SII.[15] As a first step, 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 (Table 1).[16] 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).[17]

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 EU depositors
	Private sector loans to recipients in the EU
Complexity/cross-border activity	Value of OTC derivatives (notional)
	Cross-jurisdictional liabilities
	Cross-jurisdictional claims
Interconnectedness	Intra-financial system liabilities
	Intra-financial system assets
	Debt securities outstanding

The second step of the procedure entails a national supervisory overlay. National authorities may select

[12]The following banks under the direct supervision of the SSM were identified as G-SIIs: BPN Paribas, Deutsche Bank, Groupe BPCE, Groupe Crdit Agricole, ING Bank, Santander, Socit Gnrale, Unicredit Group.

[13]The level of the SyRB may vary across institutions or sets of institutions, as well as across subsets of exposures and there is no upper limit for this buffer.

[14]All countries within the SSM implemented the capital conservation buffer, the CCyB, the G-SII and O-SIIs buffers, as well as the SyRB from the beginning of 2015. As per the initial decision in 2014/15, the phased-in capital requirement commenced from 2016 onwards, following Article 162(5) of Directive 2013/36/EU of the European Parliament and of the Council. Austria, Estonia, the Netherlands, and Slovakia introduced the SyRB at varying paces, starting from end-2014 (for an overview of national macroprudential decisions, refer to the ESRB webpage).

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

[16]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.

[17]In 2015, most countries set the threshold at the standard level (350 basis points), while two countries lowered it to 275 basis points. The thresholds for Luxembourg and Slovakia are 325 basis points and 425 basis points, respectively.

additional indicators considered adequate in capturing systemic risk in their domestic sector or in the economy.[18] This supervisory judgment is typically applied to identify (as O-SIIs) banks that were not identified based on automatic score.

In the first assessment, several countries applied supervisory judgment. Seventeen banks were identified as O-SIIs through supervisory judgment, with eleven in Germany, two in Ireland, and one each in Belgium, France, Luxembourg, and the Netherlands. Only, in a few instances, this supervisory judgment was used to reverse the O-SII identification for a bank above the threshold, primarily due to national specificities, a small and concentrated banking system, or ongoing liquidation (Table 2).[19]

From the 1st of January 2016, national authorities started to implement stricter capital requirements, typically in the form of CET1 capital buffers.[20] 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 (Sigmund, M., 2022).[21] However, the EU legislation imposes certain constraints: an upper limit of 2 percent, and for subsidiaries of G-SII or O-SII, the buffer cannot exceed the higher of 1 percent or 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.[22] 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.

[18] 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.

[19] In Estonia, AS LHV Pank and Versobank AS received relatively high total scores due to their issuance of debt securities, albeit in relatively small amounts, constituting 3 percent of AS LHV Pank's total assets and 1 percent of Versobank AS's total assets. These entities contributed to 77 percent and 1 percent, respectively, of the banking sector's total outstanding amount of debt securities. Consequently, 638 basis points and 103 basis points were added to the total scores of AS LHV Pank and Versobank AS. Without this addition, their scores remained below the 350 basis points threshold mandated by the EBA guidelines, standing at 278 basis points and 305 basis points, respectively. In Malta, although FIMBank exceeded the threshold, it did not qualify as an O-SII under the methodology applied by the national authority.

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

[21] For instance, together with the score computed for identification, national authorities considered banks' systemic importance by considering factors such as size, lending activity, and optional indicators like historical losses and GDP.

[22] 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	8 (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	6 (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 is the end-year of the first date of implementation. (1) Number of banks identified as O-SII are displayed in brackets versus the number of banks available/identified as systemic. In Austria, Raiffeisen Zentralbank is not considered in our sample as it merged with Raiffeisen Bank International. In Germany, Volkswagen Financial Services AG has been excluded given the very specific business model. In Finland, Municipality Finance Plc is excluded due to missing information. In Slovenia, four banks identified as O-SIIs were Less Significant Institutions (LSI), and some supervisory data were incomplete.

3 Data

In this section, we describe our primary data sources. We rely on two data sources: the EBA implementing technical standards on supervisory reporting (i.e., Common Reporting Framework, Corep and Financial Reporting Framework, Finrep) and the notifications from national authorities on the O-SII buffer.

We exploit the centralised European supervision setting by relying on granular confidential supervisory data, which is reported quarterly for euro area banks between the last quarter of 2014 up to the last quarter of 2017. The reporting banks include 1,300 institutions from 19 euro area countries, and includes both other systemically important banks (O-SII banks) and non-systemically important banks (non-OSII banks). Data includes information on volumes of exposures, risk-weighted-assets, impairments and expected losses, as well as indicators of capital, such as CET1 ratio or total capital ratio.[23] This data is quarterly reported to the ECB SSM under the scope of the EBA implementing technical standards on supervisory reporting (i.e., Corep and Finrep).[24]

Additionally, we rely on an internal ECB dataset on capital buffers and requirements for SSM (euro

[23]The data is collected from Corep templates C1, C2, C3, C7, C8 and C9. Corep template C8 includes also a breakdown of exposures at obligor level (grades or pools) allowing to assess the risk shifting across different buckets of obligor grades. To test for possible confounding effect related with demand factors, we use other reporting Corep templates C9, which provide information on exposures by sector at the level of the borrower/loan location (Table 6 and 7).

[24]The supervisory reporting is transmitted by banks and National Competent Authorities to the EBA and the ECB/SSM (euro area). The information is also shared with the ESRB, for a wider perimeter of EU banks.

area) banks, providing information on the O-SII capital buffer level, the associated score,[25] and the dates of notification, publication, and implementation of decisions made by national authorities. The notifications are provided by EU member states - in charge of identifying O-SIIs - to different authorities, such as the European Commission, ESRB, EBA, and ECB.[26] This dataset contains information that is crucial for our causal estimation, which lies in the distance of the score from the threshold established by national authorities for automatic identification.[27]

These two unique datasets, containing granular confidential data, allowed us to implement an exclusive assessment of the effects of higher capital buffers on lending and risk-taking. With the data at hand, more than 110 institutions, out of almost 1,300, were identified as O-SII at least once during the period considered[28] and the vast majority qualifies as Significant Institutions (SI). Our study considers O-SIIs applied at the highest level of consolidation within each country.

Indicators such as exposure at default (EAD)[29] and risk-weight density, respectively, are used to empirically study the causal impact of higher requirements (O-SII) on a bank's lending and risk-taking behaviour. To study lending, the change in the natural logarithm of a bank credit exposures is computed.[30] To assess banks' risk-taking, the change in the average risk-weights (or risk-weighted asset densities) is considered.[31] The average risk-weights, denoting the ratio of risk-weighted assets to total exposures, serve as a prevalent metric for assessing the average risk associated with bank exposures.[32]

The initial sample encompasses the nineteen countries in the euro area (SSM). However, when focusing on banks close to the threshold, the sample is narrowed down to approximately fifteen countries, which still includes all the major countries in the euro area (Table 3).[33] The descriptive evidence presented in this table shows that the distribution of the variables of interest (credit growth and risk-weights density) and controls (difference between actual and required CET1 ratio, risk-weighted assets and return-on-assets) do not differ between banks below and above the threshold and between these banks and those close to the threshold. This descriptive statistics supports the hypothesis that the potential causal effect measured at the threshold can be representative of the average causal effect for the entire sample of banks.

The distribution of CET1 by O-SII score (Figure A2)[34] shows that while there is a slight dispersion in the distance between actual and required regulatory CET1 ratio among banks above and below the threshold, it is essential to highlight that, as evident from Table 3, banks in close proximity to the threshold

[25]The annual assessment of O-SII includes the overall O-SII score for banks that are identified as systemically important.

[26]Based on Article 131(7) of the Directive 2013/36/EU (CRD IV) EU national authorities should notify, at different stages of the decision process of O-SIIs, the ECB, EBA and ESRB.

[27]The relevant threshold considered depends on the home country of the reporting bank. For those banks where the score was not communicated we estimate it based on supervisory information.

[28]The group of O-SII includes 7 Less Significant Institutions (LSIs) and one institution (an export corporation in Slovenia) which main activity is not traditional banking.

[29]The EAD, as defined by the EBA implementing technical standards on supervisory reporting, corresponds to exposures reported after incorporating value adjustments, credit risk mitigation and credit conversion factors. The EAD might be considered a measure of size, and includes both on-balance-sheet and off-balance-sheet contingent exposures and commitments (converted into equivalent on-balance-sheet amounts through credit conversion factors). Exposures are also analysed to assess other events, such the increase of exposures to sovereign debt (Becker and Ivashina, 2014); Ongena, Popov, and Van Horen, 2016) and the ECB longer-term refinancing operations (LTRO) program (Van Rixtel and Gasperini, 2013).

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

[31]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).

[32]In the case of Standard Approach exposures, risk-weights are determined based on external ratings or collateralization levels, as stipulated in Regulation (EU) No 575/2013 (CRR). For exposures under the Internal Ratings-Based Approach, risk-weights are computed in accordance with the specifications outlined in Articles 153 and 154 of the CRR.

[33]When we consider a narrow neighbour around the threshold (-50,+100) basis points the countries dropped from the sample are Slovakia, Latvia, Ireland and Greece.

[34]In Figure A2, the dots represent means within each bin. Due to the computation of optimal bins in the two charts, it is not possible to compare the number of observations used.

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*				
Households	0.058	0.264	-0.006	-0.092
	(0.51)	(1.068)	(0.31)	(0.7)
Non-financial corporations	0.020	-0.012	-0.044	-0.105
	(0.624)	(0.513)	(0.377)	(0.4)
Financial sector	-0.088	-0.049	-0.102	-0.164
	(0.794)	(0.536)	(0.415)	(0.434)
Δ *Risk-weights*				
Households	-0.033	-0.252	-0.035	0.007
	(0.281)	(1.143)	(0.109)	(0.115)
Non-financial corporations	-0.006	-0.058	0.003	0.032
	(0.203)	(0.477)	(0.118)	(0.105)
Financial sector	-0.071	-0.073	-0.045	-0.080
	(0.598)	(0.489)	(0.225)	(0.129)
CET1 ratio (actual VS required)	0.094	0.092	0.100	0.107
	(0.062)	(0.054)	(0.074)	(0.095)
Regulatory CET1 ratio	0.06	0.061	0.060	0.061
	(0.001)	(0.004)	(0.002)	(0.002)
Risk-weighted assets	0.743	1.154	0.692	0.666
	(0.505)	(2.05)	(0.267)	(0.315)
Return-on-assets	0.005	-0.001	0.003	0.001
	(0.013)	(0.009)	(0.008)	(0.01)

Notes: Data refers to the quarter following the 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 refers to the intervals used for the cross-sectional regression (see Table 4). Standard deviations are reported in parenthesis.

exhibit no significant differences in relevant observables, including additional CET1 requirements buffers. Also, the distribution of O-SII scores remains consistent across countries, with larger banks (scoring above 1500) contributing significantly, making up around 50 to 60 percent of total assets. Notably, banks in close proximity to the threshold display a consistent pattern across countries, comprising almost 40 to 50 percent of the remaining total assets in the banking system, as depicted in the right panel of Figure A1).

4 The empirical model

4.1 Identification strategy

Evaluating the impact of higher capital requirements imposed on banks identified as systemically important on their credit supply and risk-taking behaviour presents inherent challenges. 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 capitalisation, 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 likely subject to tighter capital restrictions.[35] To address these challenges, we rely on a distinctive aspect of the O-SII institutional framework, specifically the predetermined threshold used for the identification of O-SII and the subsequent application of the related capital buffer. As covered in the previous section, the EBA's guidelines for O-SII identification establish a scoring process based on four mandatory indicators: size, importance, complexity/cross-border activity and interconnectedness. National authorities use these criteria to assign a score to each bank within their jurisdiction, reflecting its systemic footprint in the national banking system. Most importantly, is the automatic identification of institutions as O-SII if their score equals or exceeds a specified threshold. Although supervisory judgment complemented the automatic calculation, the O-SII framework provides a natural setting for a regression discontinuity design.[36] 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. The EBA protocol induces a randomised 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.

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. Following Cattaneo, Idrobo and Titiunik (2017a, 2017b), a local polynomial estimator is used. 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 for a more precise estimate of the treatment effect at the cutoff.[37]

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 maximised at the threshold and declines symmetrically and linearly as the value of the score gets farther from the cutoff. Regarding 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.[38] Combined, these factors have led researchers to prefer the local linear or quadratic RD estimator.[39]

Regarding the bandwidth, we rely on a data-driven selection approach to avoid specification searching and ad-hoc decisions. Most bandwidth selection methods try to balance the bias-variance trade-off; for

[35]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.

[36]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 and Lemieux (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.

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

[38]See Gelman and Imbens (2014) for the risk of selecting high-order polynomial.

[39]Pei et al. (2022), where the authors propose and test an order-selection procedure.

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 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.[40] 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[41] and considering all the observations.

We start from estimating the short-term effects of higher capital buffers, 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 $S^{*}_{i,t}$ is the distance of the score from the threshold, $I_{i,t}$ 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).[42] The inclusion of bank and time fixed effects increases the efficiency of the estimate (Calonico et al., 2019, 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 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:

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

4.2 Validation of the identification strategy

Figure 1 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 1 confirms the use of a fuzzy design as appropriate for the setting at hand.[43] As a robustness check we drop banks which were subject to supervisory judgment and we estimate a regression discontinuity model with a sharp identification based only on the score, and results do not change significantly (Tables A8 and A9).

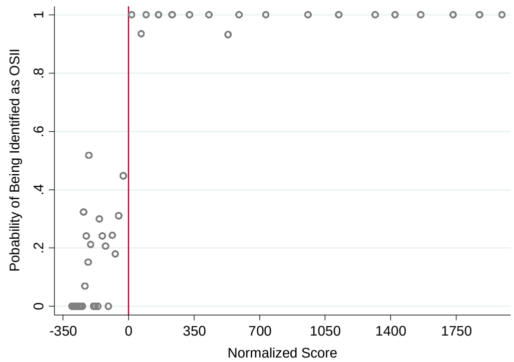
[40] Since the MSE of an estimator is the sum of its squared bias and its variance, thus this approach effectively chooses h and h' to optimise a bias-variance trade-off.

[41] 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.

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

[43] 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: 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 key assumption for causally identifying the effect of implementing the O-SII framework is based on the notion that banks do not engage in active efforts to alter or "manipulate" their scores and, consequently, their identification as an O-SII. Given that the scoring of banks is contingent on individual bank characteristics, the overall national banking system distribution, and the expert judgment of the national authority, it is unlikely that each bank could effectively "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) also depend on the behaviour of other banks. To validate this assumption, we performed different tests. First, we analyzed the distribution of 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. Figure A3 plots the density of the normalised scores, considering the overall yearly reviews (end-2015, end-2016 and end-2017), and the outcome 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 (2015), where a local polynomial density estimator is used and does not require binning the data (Figure A4). This test also reassures the absence of manipulative sorting.

Another crucial falsification test entails assessing the similarity of O-SII banks near the cutoff. The intuition is straightforward: if banks are unable to manipulate the assigned score, those positioned just above and below the cutoff should exhibit similarity in all characteristics unaffected by the treatment. In particular, predetermined covariates (e.g., CET1) should be similar across treated and untreated banks. Table A1 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 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 A5 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 randomised experiment.

It's noteworthy that during the initial implementation of the O-SII framework, the average distance for O-SII banks from the required CET1 requirement exceeded five percentage points, and for the first percentile, this distance significantly exceeded two percentage points.[44] The fact that banks were holding capital in excess of the minimum requirement does not mean that the introduction of the O-SII buffer was not a binding constraint for euro area (or SSM) banks. Regulatory changes move banks away from their intended level of excess capitalisation. Therefore, even if the requirement is not binding in the regulatory sense, the policy change may still affect lending and risk-taking behaviour as banks strive to align operations with their predetermined targets. Evidence that banks adjust their activity to meet excess-capitalisation targets is found for instance in De Jonghe et al. (2020) and Gambacorta and Mistrulli (2004). Also, following the literature (Couaillier, C., 2021; Andreeva, et al., 2020; Borsuk et al., 2020; Repullo and Suarez, 2013; Hanson et al., 2011; Brewer et al., 2008; Barth et al., 2005; Ayuso et al., 2004) banks maintain excess capitalisation, a cushion above their regulatory capital ratios, as it allows banks to absorb losses without breaching a regulatory buffer (which could trigger distribution restrictions, heightened supervisory oversight or obligations to rebuild capital) or a minimum requirement (which could trigger terminal penalties, such as license withdrawal or declaration of failure). A desire to avoid market stigma and keep some distance from the threshold for automatic restrictions on distributions may lead to unintended distortions within the capital framework by banks that operate close to the minimum requirements.

5 Results

Our results are presented in two parts. The first subsection illustrates the short-term effects of the policy change, while the subsequent subsection delves into the medium-term implications. Our results presented below remain robust across various specifications, polynomial orders, and bandwidth selection procedures.

5.1 Evidence on short-term effects

Focusing on the period after the first notification 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. Figures 2 and 3 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 normalised scores $(S^*_{i,t})$,[45] for banks in the neighbourhood of the threshold. The graphical representation does not capture the fuzziness of the O-SII identification process. However, it gives us the first representation of a potential adjustment in the outcome variables at the cutoff for banks identified as O-SII. A visual inspection of Figure 2 and 3 does not reveal a clear discontinuity in banks' credit supply or risk-taking, suggesting that the effect of identification may be negligible.

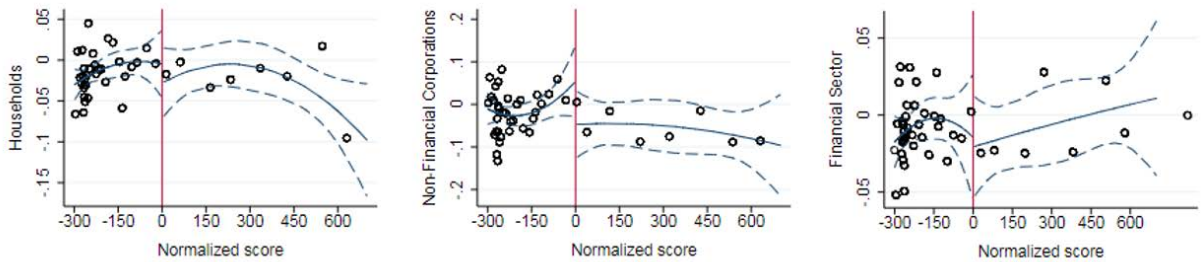
The estimates[46] for the short-term impact of the O-SII framework on euro area banks is depicted in Tables 4 and 5, for credit growth and risk-taking, respectively. The dependent variables represent the annual credit growth rate and risk-weights, respectively, measured as the change in log credit volume and the change in density of risk-weights. The outcome variables are presented for three exposure classes, such as households, non-financial corporations, and financial sector. In Tables 4 to 7, the upper panel illustrates the short-term impact of the buffer constraint at inception without controls, while the lower panel includes country and

[44] The regulatory CET1 ratio is computed as the one resulting from Pillar 1 and Pillar 2 requirements.

[45] 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.

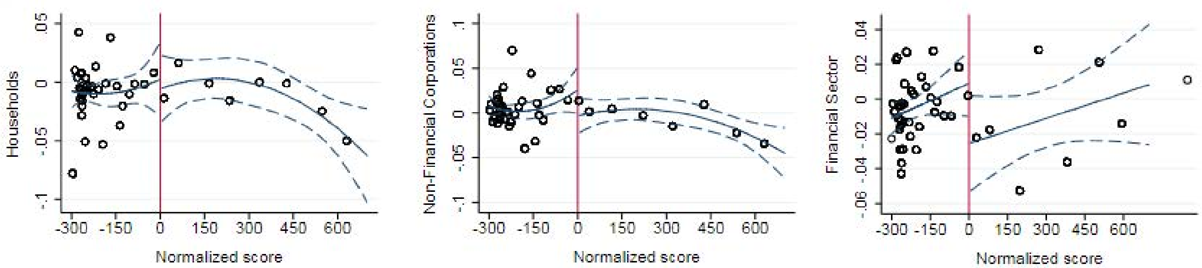
[46] To enhance the precision of our estimates and mitigate the influence of extreme values, each variable is trimmed at the 1st and 99th percentiles. The O-SII dummy interaction coefficient, along with the corresponding p-values, is then reported in each table.

Figure 2: 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 3: 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.

bank characteristics as controls, specifically those associated with the phased-in implementation of the O-SII buffer. It considers both the buffer at inception and its expected values five years after the notification.[47] In detail, we consider the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. The credit-to-GDP gap controls for potential confounding effects related with the country-specific credit cycle. It is defined as the difference between the ratio of total credit relative to GDP and its long-run statistical trend.[48]

Our results show a statistically significant reduction in lending to households and financial sector among banks subject to the O-SII buffer constraint (Table 4). A yearly increase of approximately 0.5 percent in capital buffers (for banks closer to the threshold) is associated with a decline in lending of around 0.2

[47] We also estimate the model by restricting the countries where the designated O-SII buffer was strictly positive (lower panel of Tables 4 to 7).

[48] Adding an indicator of the financial cycle allows us to better control for observed and unobserved time-varying heterogeneity at the country level. 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) (Detken et al., 2014).

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

	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
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 country level. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. It includes country and bank characteristics as controls related with the O-SII buffer implementation, which is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

percentage points for the household sector and 1.3 percentage points for the financial sector (if the increase in capital buffers is 1 percent, the corresponding decline in lending for households is estimated to be around 0.4 percentage points). These findings align with the broader literature, particularly focused on the real economy. In the existing European literature, estimates for the overall credit decline typically range between 0.02 and 1.2 percentage points (Altavilla et al., 2020; Mendicino et al., 2020; Fraisse et al., 2017; Mésonnier

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

	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
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 density. We perform local regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at country level. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. It includes country and bank characteristics as controls related with the O-SII buffer implementation, which is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

and Monks, 2015; Aiyar et al., 2014; Bridges et al., 2014; De Nicolò et al., 2014; Darracq-Pariés et al., 2011 and 2016). At the same time, the estimates from Table 5 suggest that banks identified as O-SII do not differ in terms of risk-taking from other banks, with the exception of the financial sector, which shows a statistically significant increase in risk-taking in the first panel without controls (though not consistently significant across all specifications). These results remain robust regardless of the chosen order of the polynomial (Tables A2 and A3 in the Appendix) and of the bandwidth (Tables A4, A5, A6 and A7 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 Tables 4 and 5.

To study the deferred implementation of capital surcharges characterised by a phased-in approach and divergent timelines across countries, potentially mitigating the short-term effects of O-SII buffer tightening, our model is subject to re-estimation. This involves controlling for country and bank characteristics that are correlated with the delays in implementation. Some countries deferred the application of a non-zero capital buffer beyond our sampling period, allowing banks additional time for balance sheet adjustments. Results, presented in the lower panel of Tables 4 and 5, factor in the phased-in implementation of O-SII buffer requirements, by considering the O-SII buffer at inception and its expected values five years after the notification (mainly excluding a zero capital buffer). Our estimates confirm the findings obtained from the baseline specification.

Based on these results, we can assess what would have been the credit growth for households and financial sector if the O-SII framework had not been introduced. When considering banks close to the threshold, we can estimate the counterfactual growth of credit if they were not identified as O-SII. For instance, at inception, as a counterfactual for households, this would lead to a net increase in lending by around 0.5 percentage points.[49] When evaluating the costs and benefits of implementing capital-based macroprudential policies, this potential reduction in credit supply may warrant consideration.

To control for potential difference in the demand of loans, we gather data on the country of origin of exposures (Tables 6 and 7). Relying on supervisory data, we collected a geographical breakdown of exposures and risk-weighted assets across economic sectors, including households, non-financial corporations, and financial corporations. Employing this information, we estimate the models by introducing country and bank fixed effects to control for credit demand factors. It is noteworthy that the results exhibit consistency with those obtained in our baseline specification, with exception of the households depicting a statistically significant decrease in risk-taking (for all specifications).

Finally, to draw inferences about the behaviour of larger O-SIIs, especially those with significantly higher scores, we further compare banks based on the distance of their score from the threshold to allow for a credible identification of the causal effect of being recognised as O-SII bank. To extrapolate this effect for the entire sample, we leverage the fact that in some countries, the calibration of the O-SII buffer uses different thresholds.[50] Following the approach of Cattaneo et al. (2021) and relying on the presence of multiple cutoffs, we can estimate the RD causal treatment effects away from the cutoffs that determine treatment assignments. The identification assumption is that the observed difference in lending and risk-taking between banks identified as O-SII according to a "lower" threshold and banks not identified as O-SII based on a "higher" threshold is the same for banks more distant from the threshold. Tables 8 and 9 present results that confirm the findings of the baseline specification. However, the impact on credit growth for households appears to diminish as we move away from the threshold, indicating a reduced effect for larger banks.

[49] By examining the credit growth in Table 3 for banks in proximity to the threshold and not identified as O-SIIs, along with the coefficient from Table 4, it is possible to derive an estimate for the counterfactual.

[50] In the first round of the O-SII assessment, most countries used 350 basis points as the threshold, but Austria and Luxembourg lowered it to 275 and 325, while Lithuania and Latvia raised it to 425.

Table 6: Credit Growth: Average effect of O-SII identification by economic sector and borrower's country of domicile (short-term)

	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 country level. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. It includes country and bank characteristics as controls related with the O-SII buffer implementation, which is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively. Fixed effects for banks and country of domicile of the borrower are also included.

Table 7: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector and borrower's country of domicile (short-term)

	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 density. We perform local regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at country level. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. It includes country and bank characteristics as controls related with the O-SII buffer implementation, which is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively. Fixed effects for banks and country of domicile of the borrower are included.

Table 8: Credit Growth: Average effect of O-SII identification by economic sector (short-term; external validity)

Households					
	Estimate	Bandwidth left side	Bandwidth right side	Number Observations	p-Value
Threshold = 275	-0.13***	274	486	44	0.00
Threshold = 325	-0.23***	309	599	25	0.00
Threshold = 350	-0.12***	279	2002	52	0.00
Threshold = 425	0.13	1130	1130	3	0.96
Weighted	-0.13***	.	.	124	0.00
Non-financial corporations					
	Estimate	Bandwidth left side	Bandwidth right side	Number Observations	p-Value
Threshold = 275	-0.26	274	353	46	0.45
Threshold = 325	0.34	325	599	49	0.90
Threshold = 350	0.49	230	996	34	0.06
Threshold = 425	0.33	1130	1130	8	0.38
Weighted	0.22	.	.	137	0.57
Financial sector					
	Estimate	Bandwidth left side	Bandwidth right side	Number Observations	p-Value
Threshold = 275	-0.8	272	392	45	0.12
Threshold = 325	-1.35**	325	599	48	0.01
Threshold = 350	-1.14**	277	1898	52	0.01
Threshold = 425	-1.19**	1130	1130	8	0.01
Weighted	-1.11***	.	.	153	0.00

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 bandwidths. We consider the first O-SII assessment, where national thresholds are not normalised, employing a multi-cutoff regression discontinuity design for extrapolation. No controls are included. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table 9: Risk-Taking: Average effect of O-SII identification by economic sector (short-term; external validity)

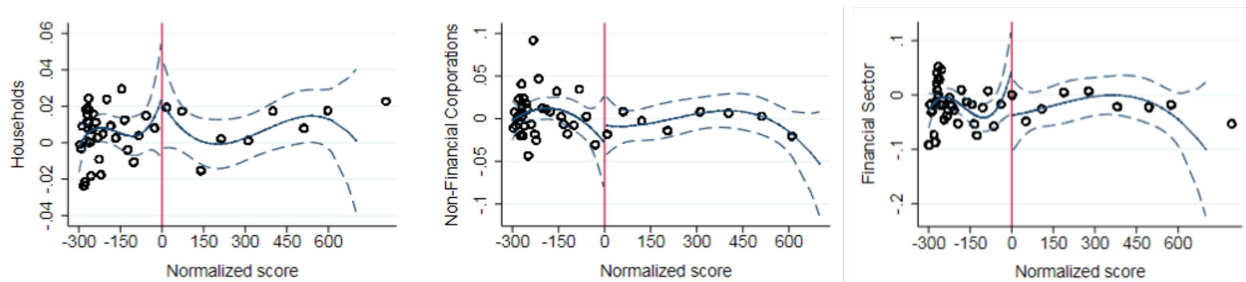
Households					
	Estimate	Bandwidth left side	Bandwidth right side	Number Observations	p-Value
Threshold = 275	0.02	274	639	43	0.62
Threshold = 325	0.03	324	599	35	0.34
Threshold = 350	-0.03	345	1090	211	0.05
Threshold = 425	0	1130	1130	3	0.21
Weighted	-0.01	.	.	292	0.37
Non-financial corporations					
	Estimate	Bandwidth left side	Bandwidth right side	Number Observations	p-Value
Threshold = 275	-0.08	274	540	106	0.59
Threshold = 325	0.09	325	599	8	0.25
Threshold = 350	0.02	327	1388	209	0.73
Threshold = 425	-0.09	1130	1130	29	0.84
Weighted	0.02	.	.	209	0.38
Financial sector					
	Estimate	Bandwidth left side	Bandwidth right side	Number Observations	p-Value
Threshold = 275	0.02	274	447	45	0.72
Threshold = 325	0.02	325	599	55	0.60
Threshold = 350	0.16	249	764	37	0.14
Threshold = 425	0.06	1130	1130	8	0.52
Weighted	0.07	.	.	145	0.23

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 density. We perform local regressions with a triangular kernel using both the MSE-optimal. We consider the first O-SII assessment, where national thresholds are not normalised, employing a multi-cutoff regression discontinuity design for extrapolation. No controls are included. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

5.2 Evidence on the medium-term effects

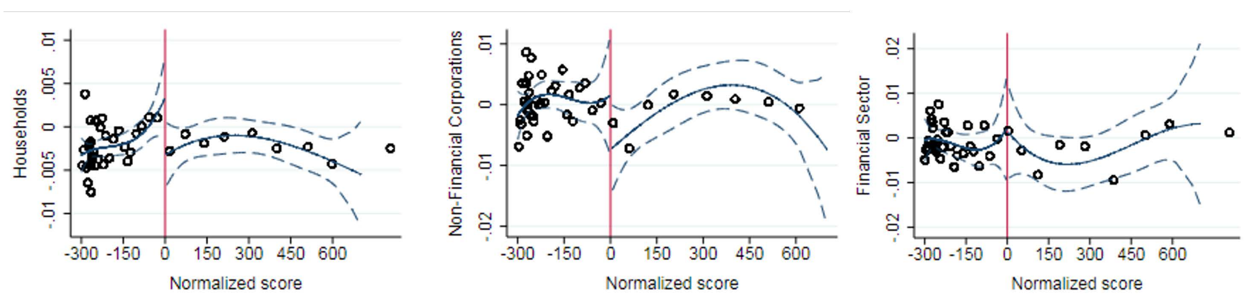
To assess the O-SII effect on the medium-term allows us to track banks' behaviour controlling for time-varying capital requirements and observable banks' characteristics. We start by presenting graphically changes in the credit supply and banks' risk-taking for banks identified as O-SII. Figures 4 and 5 show the unconditional quarterly change in credit and risk-weight density of banks around the threshold, from end-2015 to end-2017. In particular, we show a scatter plot for each outcome variable against the normalised 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 in the medium-term. Nevertheless, it is possible to detect an adjustment when looking at bank risk-taking, in particular for households.

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 risk-weights 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 end-2015 to end-2017, for banking institutions in 19 euro area countries, of which more than 110 banks were identified as O-SII. We propose two specifications (Tables 10 and 11) to identify the medium-term effects on banks' risk-taking behaviour and credit supply. The first specification exhibited in the upper panel presents the estimates for the impact of O-SII identification, controlling only for non-observable banks' characteristics and quarter fixed effects. The second specification, presented in the lower panel, includes control variables such as lagged values of the yearly credit-to-GDP gap, the distance between actual and required CET1 ratio, the return-on-assets 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 more banks were identified as O-SII in 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 annual assessment were considered as "treated" in the analysis.

Table 10 presents the results for credit supply, defined as the quarterly credit growth rate as the change in the log of a banks' credit volume. Results show that O-SII banks do not reduce their supply of credit in the medium-term, where exposures to economic sectors do not differ between banks identified as O-SII and others. Our results also hold when including country- and bank-specific controls to address correlation concerns regarding differences in banks' characteristics and changes in credit demand. Table 11 presents the results for risk-taking, defined as quarterly changes in risk-weights density. Results show that if we account for observable and non-observable characteristics of banks, countries and time fixed effects, banks identified as O-SII reduce, in the medium-term, their quarterly average risk-taking by around 0.02 to 0.04 percentage points in the households and financial sector, compared to those just below the threshold. The decrease in the risk-taking is significant for households in all specifications. Figure A6 suggests that the observed reduction in risk-weights may not be driven by a corresponding increase in collateral backing loans.[51] The absence of a substantial rise in the median value of collateral as a percentage of underlying exposure for O-SII banks over time indicates that the medium-term reduction in risk-weights may be attributed to changes in lending standards and risk management practices rather than collateralisation trends. Note that these findings follow Konietschke et al. (2022), where banks, under stress test-related capital requirements, tend to redirect credit from riskier to safer borrowers in the household sector. This strategic shift is aimed at enhancing safety towards safer borrowers, albeit at the cost of profitability in this sector.

Based on this evidence, results suggest that the introduction of the O-SII framework had limited costs as it contained the reduction in credit supply, while still achieving risk reduction benefits. In terms of real effects, we find that banks subject to the O-SII buffer shifted lending towards safer borrowing in the household sector, maintaining SME financing within the corporates segment. Banks also adjusted average risk-weights downward mainly in the household sector, which could be attributed to improved risk management practices, including lower loan-to-value ratios, enhanced consideration of eligible collateral, and improved creditworthiness due to favourable macroeconomic conditions. The derisking within the household sector can be explained by banks' commitment to maintain profitability, a critical factor in the EU banking system amidst a low-interest-rate environment (the period of our study). This environment, although potentially detrimental to profits according to Altavilla et al. (2018), was offset by improved macroeconomic conditions over the study horizon, leading to reduced provisions and risk. In other words, banks decreased their lending (short-term) and risk position (medium-term) towards safer options in the households, allowing for compliance with the capital buffer requirement while avoiding a strong reduction in profitability in case banks were deleveraging via firms.

[51] Following the EU legislation (CRR), and based on the credit risk standardised approach, the risk-weight for retail portfolios is 75 percent. However, exposures that are secured by residential properties are assigned to a risk-weight of 35 percent. 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 10: 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 country level. The upper panel presents the medium-term impact of the buffer constrain without controls. The estimates in the lower panel are conditional on the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio, banks' risk-weight density and return-on-assets. Bank- and quarter-specific fixed effects are used. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table 11: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector (medium-term)

	Households	Non-financial corporations	Financial sector
Δ*Risk-weights*			
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-weights*			
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 country level. The upper panel presents the medium-term impact of the buffer constrain without controls. The estimates in the lower panel are conditional on the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio, banks' risk-weight density and return-on-assets. Bank- and quarter-specific fixed effects are used. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

6 Conclusions

This research contributes uniquely to the existing literature by leveraging in the EU policy, offering valuable insights into the longstanding debate on the effects of bank capital regulation on credit supply and risk-taking. We exploit the EU framework to identify the causal impact of higher capital buffer requirements on banks' lending and risk-taking behaviour. The O-SII identification under the EU framework relies on a scoring process, automatically designating a bank exceeding a predetermined threshold as systemically important. This scoring mechanism allows us to exploit the discontinuity created by the O-SII identification process. The key assumption underlying our approach is the existence of a narrow window around the threshold, where each bank's assignment above or below the threshold is probabilistic, thus enabling 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. We employ a regression discontinuity design (Cattaneo, Idrobo and Titiunik, 2017a, 2017b) to assess the impact of the O-SII capital regulation on the behaviour of banks with scores around the threshold. In particular, we build on the fuzzy regression discontinuity design that accommodates the probabilistic nature of treatment assignment, aligning with the O-SII framework.

This paper contributes to the discussion regarding the effects of higher capital requirements on bank lending and risk-taking behaviour, offering policymakers valuable insights to tailor their policy actions. Leveraging the SSM confidential centralised supervisory data, our findings reveal a short-term reduction in credit supply to households and financial sector following the introduction of the O-SII framework, coupled with a medium-term shift towards less risky borrowers, particularly in the household sector. Our study aligns with prior research, including De Jonghe et al. (2020), Berrospide and Edge (2019), Gropp et al. (2018), Fraisse et al. (2017), Mésonnier and Monks (2015), Aiyar et al. (2014, 2016), Bridges et al. (2014), and Hanson et al. (2011), which consistently find banks cutting lending to meet higher capital requirements. Similarly, in line with Buch and Prieto (2014) and Bridges et al. (2014), we find a temporary cut in loan growth post-capital requirement hikes, recovering in the medium- and long-term. The non-significant impact on credit growth for banks near the threshold in the medium-run and the smoothing of credit supply cycles align with Furlong and Keeley (1989) and Jiménez et al. (2015, 2017). Additionally, the positive disciplining effect in the household sector is supported by Konietschke et al. (2022), highlighting a shift towards safer borrowers. The risk-taking adjustment, potentially facilitated by improved risk management practices, ensures an overall disciplining effect while maintaining some profitability, especially in the household sector. The lack of a significant impact on corporate lending may be attributed to banks' efforts to uphold satisfactory returns in response to the extended period of weak profitability in the European banking industry from mid-2012 until 2021.

From a policy perspective, our findings suggest that capital requirements that target the regulatory capital ratio may yield a favorable disciplining impact by mitigating risk-taking, with only a minimal adverse effect on the real economy.

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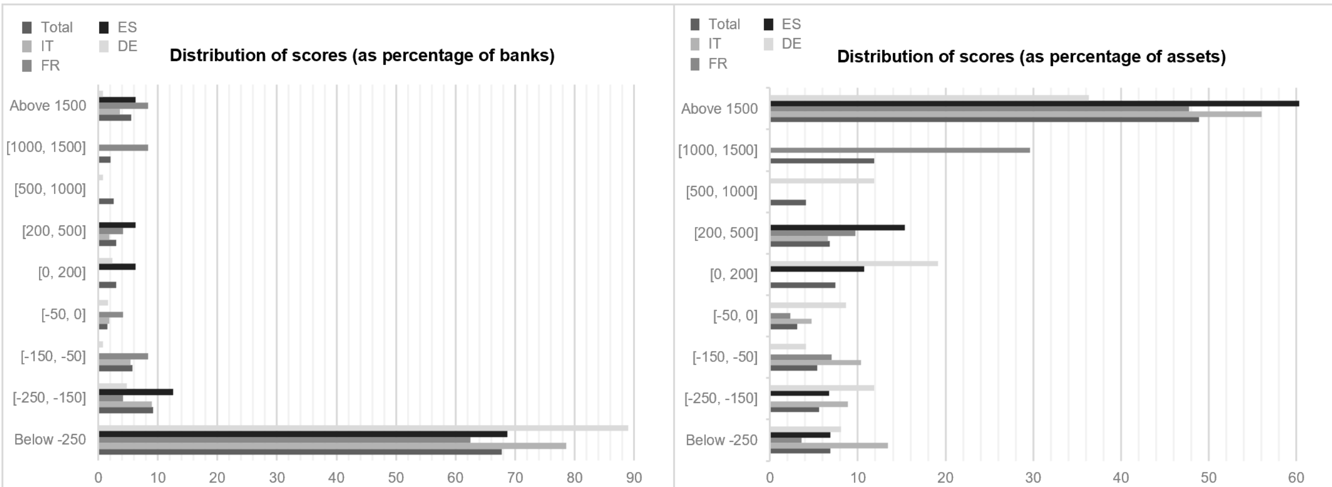
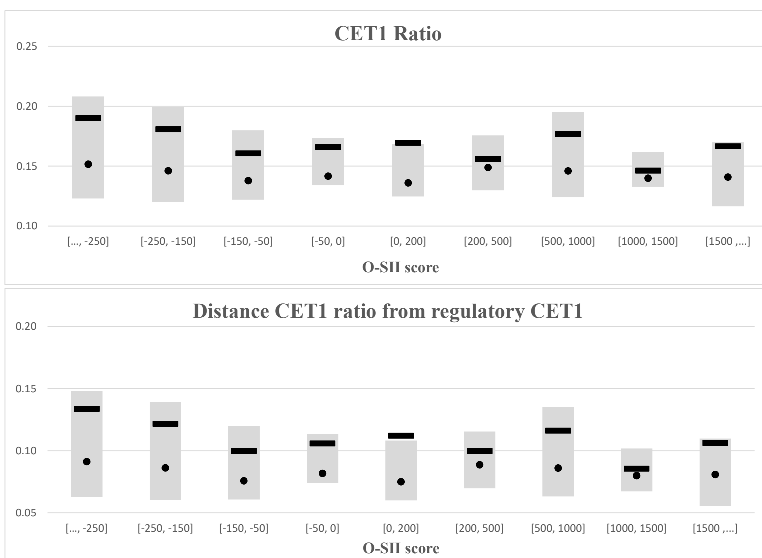
Appendix A. Additional material

Figure A1: Distribution of O-SII scores as percentage of banks and assets



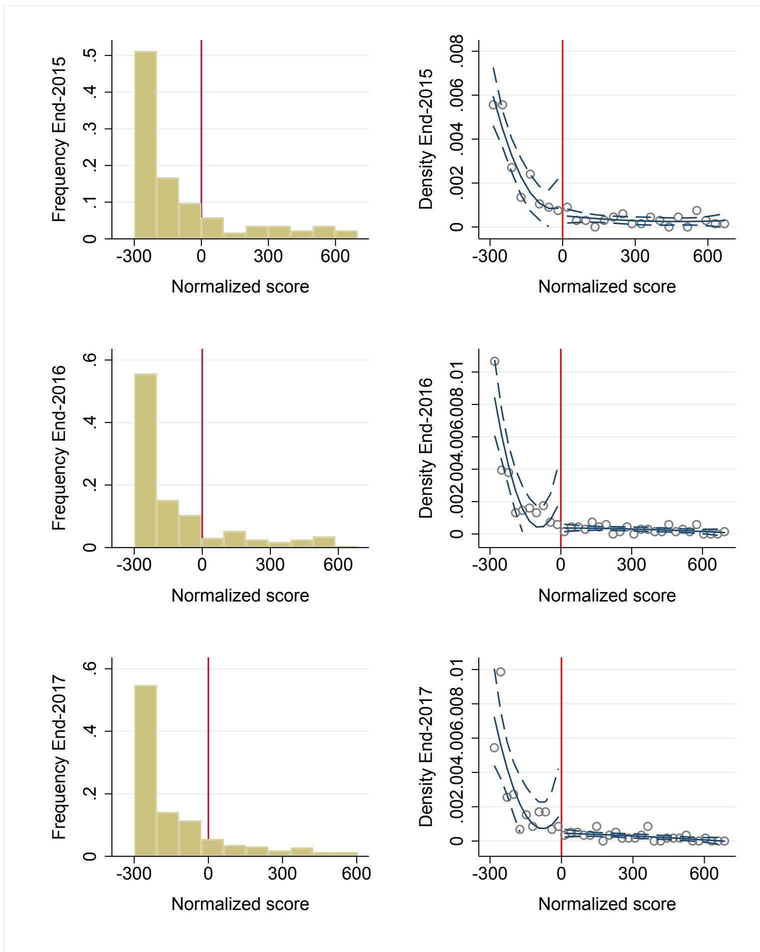
Notes: Distribution of O-SII scores as percentage of banks (lhs) and as percentage of total assets (rhs). Data refers to the quarter following the decision regarding the identification of O-SII banks.

Figure A2: Distribution of CET1 ratio by O-SII score



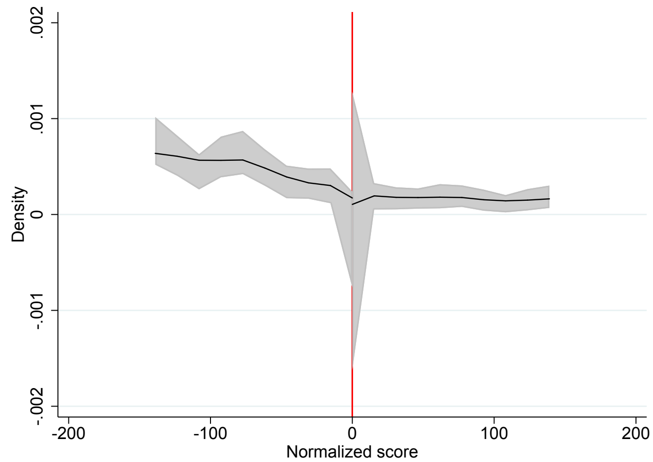
Notes: Distribution of CET1 ratio (upper panel) and distance between CET1 ratio and required regulatory CET1 ratio (lower panel) by O-SII score bucket.

Figure A3: Cross-sectional test of continuity of the score's density



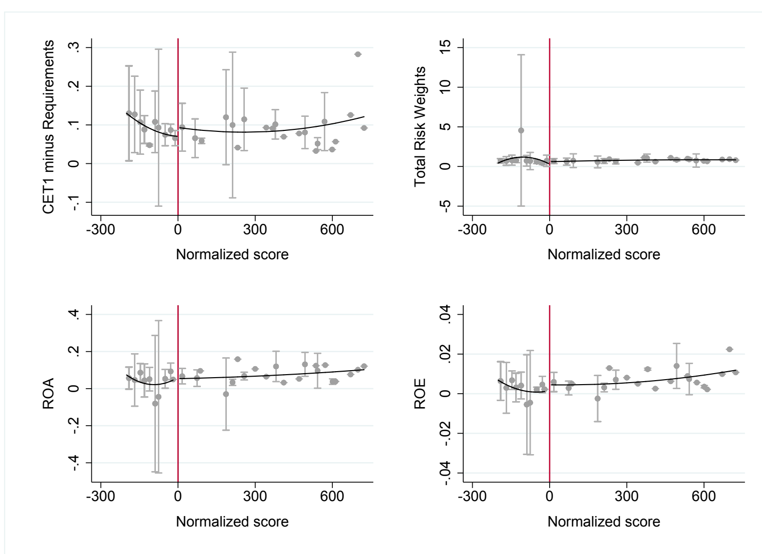
Notes: The graphs on the left-hand side exhibit the frequency of normalised scores, while the graphs on the right-hand side represent the McCrary test of density continuity for each of the yearly O-SII reviews. A weighted kernel estimation is performed separately on each side of the cutoff.

Figure A4: 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, 2015). For this test, we considered the scores at end-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 A5: 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 end-2015. The test statistic is constructed using a polynomial of order 2.

Table A1: Test of continuity of the covariates at the threshold (date 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 remain robust when employing the optimal bandwidth in the equation used to test the continuity of the covariates.

Table A2: Credit Growth: Average effect of O-SII identification by economic sector (short-term)

	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 country level. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. The O-SII buffer is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A3: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector (short-term)

	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 country level. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. The O-SII buffer is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A4: Credit supply: Average effect of O-SII identification by economic sector for different bandwidths (short-term)

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 normalised 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 annual 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 are conditional on the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A5: Risk-taking (risk-weights): Average effect of O-SII identification by economic sector for different bandwidths (short-term)

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 normalised 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 annual 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 are conditional on the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A6: 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 are conditional on the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio, banks' risk-weight density and return-on-assets. Bank- and quarter-specific fixed effects are used. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A7: Risk-taking (risk-weights): Average effect of O-SII identification by economic sector for different bandwidths (medium-term)

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 are conditional on the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio, banks' risk-weight density and return-on-assets. Bank- and quarter-specific fixed effects are included. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Table A8: Credit Growth: Average effect of O-SII identification by economic sector and borrower's country of domicile (short-term; excluding banks under supervisory judgment) - Sharp RD

	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-0.201***	0.167**	-0.896***
(p-value)	0.006	0.040	0.000
MSE-optimal bandwith $[-h, h']$	[-58, 431]	[-108, 325]	[-91, 1134]
Observations	39	63	90
Order of polynomial	1	1	2
Treatment effect	-0.219***	0.158	-1.172***
(p-value)	0.005	0.082	0.000
CER-optimal bandwith $[-h, h']$	[-48, 361]	[-91, 272]	[-74, 925]
Observations	39	63	90
Order of polynomial	1	1	2
Controls	None	None	None
	Households	Non-financial corporations	Financial sector
Δ *Log Credit*			
Treatment effect	-1.634***	0.141***	-0.781**
(p-value)	0.000	0.000	0.041
MSE-optimal bandwith $[-h, h']$	[-101, 39]	[-52, 458]	[-143, 181]
Observations	18	26	34
Order of polynomial	1	2	2
Treatment effect	-1.634***	0.141***	-1.033**
(p-value)	0.000	0.000	0.046
CER-optimal bandwith $[-h, h']$	[-101, 39]	[-52, 458]	[-117, 148]
Observations	18	26	23
Order of polynomial	1	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 linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at country level. The sample comprises only banks on which supervisory judgment was not applied. We consistently employ a sharp regression discontinuity estimation. We used both first and second polynomial orders to avoid a lack of observations in the estimation. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. The O-SII buffer is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

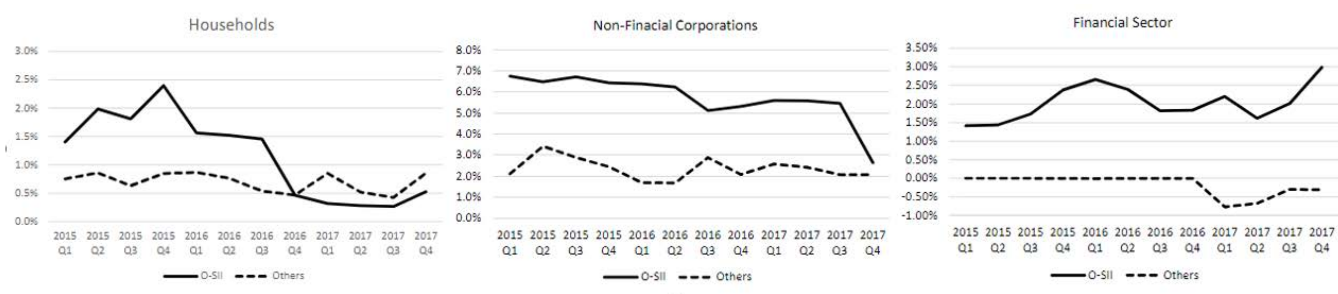
Table A9: Risk-Taking (risk-weights): Average effect of O-SII identification by economic sector and borrower's country of domicile (short-term; excluding banks under supervisory judgment) - Sharp RD

	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	0.005	-0.048	-0.035
(p-value)	0.748	0.543	0.252
MSE-optimal bandwith $[-h, h']$	[-132, 1334]	[-201, 1150]	[-205, 653]
Observations	58	85	68
Order of polynomial	2	2	2
Treatment effect	0.002	-0.007	-0.053**
(p-value)	0.903	0.938	0.017
CER-optimal bandwith $[-h, h']$	[-108, 1089]	[-164, 938]	[-168, 534]
Observations	49	68	50
Order of polynomial	2	2	2
Controls	None	None	None

	Households	Non-financial corporations	Financial sector
Δ *Risk Weights*			
Treatment effect	-0.042***	0.104	-0.065
(p-value)	0.001	0.108	0.089
MSE-optimal bandwith $[-h, h']$	[-308, 962]	[-169, 1276]	[-163, 1187]
Observations	93	54	50
Order of polynomial	2	2	2
Treatment effect	-0.049***	0.09	-0.054
(p-value)	0.002	0.217	0.200
CER-optimal bandwith $[-h, h']$	[-253, 789]	[-138, 1046]	[-134, 973]
Observations	65	47	43
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 linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths. Standard errors are clustered at country level. The sample comprises only banks on which supervisory judgment was not applied. We consistently employ a sharp regression discontinuity estimation. We used second polynomial orders to avoid a lack of observations in the estimation. The upper panel presents the short-term impact of the buffer constrain at inception without controls. The lower panel of results includes the following controls: one year lagged value of the credit-to-GDP gap for each country, distance between actual and required CET1 ratio and banks' risk-weight density. The O-SII buffer is considered at inception and its expected values five years after the notification. ***, **, and * denote significance at the 1, 5 and 10 per cent level, respectively.

Figure A6: Value of the collateral over the exposure amount (end-2015 to end-2017)



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

Appendix B. Causal identification with regression discontinuity

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.[52] 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.[53] After the notification is issued (i.e., for $t \geqslant \tau$), the treatment status $I_{i,t}$ changes, where banks with a score above a predetermined country-specific threshold are qualified as O-SII and may be charged with an additional capital requirement. It should be noted that the introduction of the O-SII capital buffers has been often postponed in time and phased-in over several time periods. However, it is plausible that banks already started adjusting their balance sheets as soon as they were notified of their classification as an O-SII. Therefore, we assume the adjustment period to have started just after the notifications have been issued by the national authorities.

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.[54] 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 et al. (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

[52] 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.

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

[54] The original motivation for a local randomisation 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.

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.[55]

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 distance between actual and required CET1 ratio, the risk-weights density, the return-on-assets 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. 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.[56] This implies that the probability of being identified as O-SII changes discontinuously (Figure 1) at the threshold, leading to the application of a fuzzy regression discontinuity model:

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

In this setup, it is possible to take advantage of the discontinuous change in treatment assignment at the threshold to measure the causal impact of the treatment on the outcomes of interest. Following Hahn et al. (2001), let $Y^+ = \lim_{\varepsilon \to 0^+} E\left[Y_{i,t}|\ S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$ and $Y^- = \lim_{\varepsilon \to 0^-} E\left[Y_{i,t}|\ S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. 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 randomised, the ratio π_{FRD} identifies the local average treatment effect (LATE) of a bank being designated as O-SII on the outcome of interest.

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

[56] 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.