EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

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How do banking groups react to macroprudential policies? Cross-border spillover effects of higher capital buffers on lending, risk-taking and internal markets

No 2497 / November 2020

Abstract

We study the impact of macroprudential capital buffers on banking groups' lending and risk-taking decisions, also investigating implications for internal capital markets. For identification, we exploit heterogeneity in buffers applied to other systemically important institutions, using information from three unique confidential datasets, including information on the EBA scoring process. This policy design induces a randomized experiment in the neighborhood of the threshold, which we use to identify the effect of higher capital requirements by comparing the change in the outcome for banks just above and below the cut-off, before and after the introduction of the buffer. The analysis is implemented relying on a fuzzy regression discontinuity and on a difference-in-differences matching design. We find that, when parent banks are constrained with higher buffers, subsidiaries deleverage lending and risk-taking towards non-financial corporations and marginally expanded lending towards households, with negative effects on profitability. Also, we find that parents cut down on holdings of debt and equity issued by their subsidiaries. Our findings support the hypothesis that higher capital buffers have a positive disciplinary effect by reducing banks' risk-taking while having a (temporary) adverse impact on the real economy through a decrease in affiliated banks' lending activity. Therefore, to ensure the effectiveness of macroprudential policy, it is essential that policymakers assess their potential cross-border effects.

Keywords: Macroprudential policy, Capital buffers, Lending, Risk-taking, Internal capital markets.

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

Non-Technical Summary

The global financial crisis which erupted in August 2007 revealed the limitations of the supervisory framework in ensuring the resilience of the banking system to adverse macro-financial shocks. In the euro area, this led to changes in the supervisory institutional setting by moving to a centralised banking supervision, while, at the same time, the European Union (EU) built up the macroprudential policy toolkit to address risks of a systemic nature.[1] In this study, we are focused on the other systemically important institutions buffer (OSII), which aims to reduce moral hazard and misaligned incentives by strengthening the resilience of "too big to fail" institutions. Due to the international dimension of the banking sector, domestically oriented macroprudential policies might create unintended cross-border spillover effects. Banking groups constrained with higher capital requirements might restructure, through subsidiaries, their internal capital markets or negatively reduce the local supply of credit.[2]

In this paper, to explicitly analyse leakages of policy measures, we study the impact of higher capital buffers, namely the OSII buffers, on banking groups' lending and risk-taking and its further implications on the groups' internal capital markets. For identification, we exploit the heterogeneity in buffers applied to other systemically important banks, using the information from three unique confidential datasets, including the European Banking Authority (EBA) framework.[3] The EBA setting relies on a two-step procedure: i) a scoring process, which automatically qualifies a bank, with a score above a predetermined threshold, as systemically important;[4] and ii) a supervisory expert judgement, which may qualify some banks below the threshold as systemically important. The EBA scoring process induces for a randomized experiment in a neighborhood of the threshold, allowing to identify the effect of higher capital requirements by comparing the change in the outcome of banks just above and below the cutoff, before and after the introduction of the additional capital surcharge. This policy design allows us to implement an exclusive assessment, relying on both a fuzzy regression discontinuity and a difference-in-differences matching designs, which exploit the regulatory change and the discontinuity induced by the OSII identification process. The fuzzy regression discontinuity design is the econometric setup to assess the effects of higher capital buffers on banking groups' lending, risk-taking and profitability and the difference-in-differences matching[5] is used to assess the implications of higher capital requirements in the internal capital markets of banking groups.

[1] From a financial stability perspective, it was also important to mitigate a potential increase of banks' risk-taking due to monetary policy easing.

[2] Macropudential measures are expressed in ratios, where banking groups can accommodate such higher capital requirements by reducing lending and risk-taking in subsidiaries of the group, thus freeing up capital at the consolidated level.

[3] Under Article 131(3) of the Directive 2013/36/EU ('CRD IV') and the EBA Guidelines (EBA/GL/2014/10).

[4] A bank is designated as OSII if the score is equal or higher than 350 basis points. To account for the specificities of each EU member state's banking sector and the resulting statistical distribution of scores, authorities may raise the threshold up to 425 basis points or decrease it to 275 basis points.

[5] This alternative identification strategy is used given the less populated intra-group holdings dataset.

In our study we establish two main findings. First, subsidiaries of banking groups whose parent has been identified as systemic and, subsequently, constrained with a higher capital buffer (OSII), reduced credit supply and risk-taking towards non-financial corporations and marginally expanded lending supply towards households. At the same time, results show a reduction in affiliated banks' profitability explained by the banks' re-balancing behaviour for lending and risk-taking, i.e. credit shifting towards safer options. Second, lending and holding dynamics within banking groups are also affected when a parent bank is identified as systemically important, since our results indicate that parents cut down on holdings of both debt and equity issued by their subsidiaries.

In terms of financial stability implications, our results suggest that the implementation of higher capital requirements at the consolidated level leads to a reduction in lending and risk-taking in the local credit markets, particularly towards non-financial corporations. We observe that this macroprudential policy, aimed at strengthening the resilience of banks, can also trigger an adverse effect in the real economy (as suggested also by Admati et al. (2015) and Cappelletti et al. (2019)).[6] Also, our results follow the existent literature on the behaviour of the banking groups' internal markets (Campello (2002), Cetorelli and Goldberg (2012), Mili et al. (2017) and Buch and Goldberg (2017)) where banking groups react to a more stringent requirements by cutting down liquidity towards domestic and cross-border subsidiaries, therefore concentrating it around the parent. At the same time, as cited by Cappelletti et al. (2019), Gersbach and Rochet (2017)[7] and Repullo (2004), higher capital requirements can reduce banks' gambling incentives, leading to a "prudent equilibrium". Our findings contribute to this debate suggesting that higher capital buffer requirements have a positive disciplining effect by reducing banks' risk-taking, while having at the same time an adverse impact on the real economy via reduction of affiliated banks' lending supply to non-financial corporations and consequent profitability of banks. Thus in terms of policy action, as suggested by Hanson et al. (2011) and Gropp et al. (2019), targeting the absolute amount of new capital to be raised[8] instead of the capital ratio could mitigate the temporary adverse impact in the real economy, along with the potential optimisation of the risk-weighted-assets. Also, cross-border spillover effects should be factored in when assessing and calibrating macroprudential policy measures to ensure the effectiveness and consistency of macroprudential policy. It is essential that policymakers coordinate potential cross-border effects in the policy measures adopted by national authorities, in order to allow other cross-border authorities to adopt suitable reciprocating macroprudential measures.

[6]Banks tend to comply with higher capital requirements by dampening down their risk-weighted-assets, i.e. by deleveraging lending and risk-taking. Banks can increase capital ratios by: increasing capital (the numerator of the capital ratio) or by decreasing risk-weighted-assets (the denominator of the capital ratio) (Gropp et al. (2019)).

[7]Authors show that imposing stricter capital requirement in good states corrects capital misallocation, increases expected output and social welfare.

[8]As applied in the U.S. stress-tests conducted in 2009 (Hirtle et al. (2009)).

1 Introduction

The financial crisis, prior to the summer of 2007, emphasised the considerable gap between financial stability monitoring and assessment tasks, and their translation into effective policy actions. In particular, the supervisory framework existent was very limited in ensuring the resilience of the banking system to adverse macro-financial shocks. In this context, imbalances were building up in the financial system in the years prior to the summer of 2007, without any financial stability assessment and intervention. In particular, it was recognized that the supervisory and regulatory framework did not address system-wide risks, which lead to a comprehensive reform in both micro supervision and macroprudential policy. For this reason, the great financial crisis led to changes in the supervisory institutional setting, in the euro area, by moving to a centralised banking supervision, while, at the same time, the European Union (EU) built up the macroprudential policy toolkit to address risks of a systemic nature. Through macroprudential policy, the objective is to increase the resilience of the financial system, contain the build-up of systemic vulnerabilities within the financial system arising from interlinkages, common exposures, and the critical role of intermediaries in key markets (IMF-FSB-BIS, Elements of Effective Macroprudential Policies (2016)). In this paper, we are focused on the macroprudential measure related with other systemically important institutions capital buffer (OSII) which aims to reduce moral hazard and misaligned incentives by strengthen the resilience of "too big to fail" institutions. This additional capital requirement cushions the systemic impact of misaligned incentives by strengthening the resilience of systemic banks to absorb losses and thus reduces contagion risk (ESRB Handbook (2018)). However, this macroprudential policy can generate unintended cross-border spillovers, due to the international dimension of the banking sector. Banking groups constrained by higher capital requirement might restructure, through subsidiaries, their internal capital markets or negatively reduce the local supply of credit, thus freeing up capital at the consolidated level.

There are some key challenges is making a holistic assessment of a macroprudential stance (Stein (2014), Galati and Moessner (2013), Woodford (2012) and Taylor (2009)) since it requires an understanding of the suitability of a policy with respect to the objective of containing systemic risk and of the interactions between macroeconomic and macroprudential instruments. Despite many challenges, increasing efforts have been made in recent years to fill these gaps. The International Monetary Fund (IMF) database of macroprudential policies introduced by Lim et al. (2011) found its most recent continuation in the Prudential Instrument Database developed for the needs of the International Banking Research Network (IBRN) and described by Cerutti et al. (2016). The database was later integrated in the IMF Macroprudential Policy (iMaPP) database.[9] Cerutti et al. (2017a) built a comprehensive cross-country database on prudential instruments and use an aggregate index to estimate the potential spillovers. Shim et al. (2013) collected data on policy actions related with the housing markets. Vandenbussche et al. (2012) collected information on macroprudential policy measures related to house prices in a database for 16 countries in Central, Eastern, and South-Eastern Europe. Federico et al. (2012a) constructed a dataset on legal reserve requirements for 52 countries, of which 15 are industrial and 37 developing countries. Budnik and Kleibl (2018) built a new comprehensive data set on policies of a macroprudential nature in the banking sectors for the 28 member states of the EU between 1995 and 2014. Following recent progress on data collections, some literature has attempted to shed light on the link between capital regulation and the cost of banks' capital and credit supply, which in turn can have an impact on the real economy (Borio and Zhu (2008), Claessens et al. (2013), Galati and Moessner (2013), Cerutti et al. (2015, 2016, 2017a, 2017b), Jiménez et al. (2017)).

Macroprudential measures implemented by national authorities domestically may have cross-border repercussions. Policy measures targeting areas of the domestic financial system can easily propagate across borders. Buch and Goldberg (2017) find that most of the regulatory policy measures have been associated with both positive and negative spillovers. Authors show that the effects of prudential instruments on lending are conditional on both banks' characteristics and internal capital markets. Aiyar et al. (2014) find a negative and statistically significant effect of changes to banks' capital requirements on cross-border lending. Authors also show that the negative cross-border credit supply response is significantly lower in "core countries" than in others. Also, authors indicate that banks tend to cut back cross-border credit to other banks (including foreign affiliates) more than credit to firms and households. Aiyar, Calomiris and Wieladek (2014a) conclude that leakages weaken policy effectiveness in the domestic market. Aiyar, Calomiris and Wieladek (2014b) show that foreign-regulated branches are an important source of credit substitution. Ongena, Popov and Udell (2013) show that tighter restrictions on bank activities in home countries lead cross-border subsidiaries to extend loans to higher risk corporations loans. Beirne and Friedrich (2017) find some evidence of geographical reallocation amounting to outward spillovers. Claessens (2016) suggest that macroprudential policies can create cross-border spillover effects via the bond markets. Bengui (2014), Jeanne (2014), Korinek (2014) and Kara (2016) develop finite horizon models, where banks take decisions on investments, liquidity and capital allocation ex-ante to the realization of a regulatory induced macro-financial risk. For a broader discussion on the topic, Kok and Reinhardt (2020) provide a more comprehensive conceptual framework for cross-border spillover effects of macroprudential policies. In this paper, we explicitly analyse cross-border spillover effects of macroprudential measures, by studying behavioural changes, in terms of lending, risk

[9] Available at https://www.elibrary-areaer.imf.org/Macroprudential/Pages/iMaPPDatabase.aspx.

taking and internal resources allocation of banking groups, once the parent has been constrained with higher capital requirements. Ideally, cross-border spillover effects should be factored in when assessing and calibrating macroprudential policy measures. To ensure the effectiveness and consistency of macroprudential policy it is essential that policymakers coordinate potential cross-border effects in the policy measures adopted by national authorities. This is relevant since national authorities can adopt suitable reciprocating macroprudential measures to address those cross-border spillover effects. This follows Beck and Wagner (2016) and Colliard (2020) where they discuss the benefits of coordinating prudential supervision beyond national borders in order to internalise cross-border externalities.

This paper causally assesses the impact of higher capital requirements by exploiting the institutional setting used to apply additional capital surcharges to systemic banks. Our aim is to assess banking groups' lending and risk-taking decisions and to identify behavioural changes within a group' internal capital markets, under a more stringent capital regulation. Moreover, we also look at the banks' profitability as an indicator for potential policy implications, which might arise from changes in lending and risk-taking. We contribute to the existing literature by exploiting the EU institutional setting for the application of OSII buffers and assess the impact of this capital surcharge on the treated banking groups. Since the beginning of 2015, 119 entities were identified as OSII and constrained with supplementary requirements concerning the common equity tier 1 (CET1) ratio (of which 38 were OSII parent banks). Although the policy was implemented with different methodologies and different phase-in arrangements, the protocol for the identification of the OSII has been established in the European Banking Authority (EBA) guidelines.[10] Under the EBA guidelines, each bank receives a score based on four mandatory indicators which should reflect its systemic importance. Banks with a score above a country specific threshold are automatically designated as O-SII.[11]

Recent literature has been studying the relation between higher capital requirements and economic growth. The focus of most papers is on the effects of higher capital buffer requirements on the cost of banks' equity, lending and risk-taking, which implies an impact on the real economy. Cappelletti et al. (2019), Aiyar et al. (2014) and Gropp et al. (2019) find that banks constrained with higher capital requirements tend to increase their capital ratios not by raising their levels of equity, but by reducing their credit supply. Cappelletti et al. (2019) refer that adequate phase-in arrangements, for instance, may allow banks to smoothly adjust their balance sheets, thereby limiting possible backlashes of tighter restrictions on the real economy. Noss and Toffano (2016) show that an increase in capital ratios of banks operating in the UK is associated with a reduction in lending. Bridges et al. (2014) show that in the year following an increase in

[10] Under Article 131(3) of the Directive 2013/36/EU ('CRD IV') and the EBA Guidelines (EBA/GL/2014/10).

[11] As explained in Section 2.1, national authorities also have the possibility to implement the supervisory judgment, to identify as OSII banks falling below the automatic score threshold.

capital requirements, banks deleveraged loans to commercial real estate, other corporates and households. Martynova (2015) suggests that banks facing higher capital requirements can reduce credit supply, as well as decrease credit demand by raising lending rates which may slow down economic growth. However, Buch and Prieto (2014) find no evidence for a negative impact of bank capital on business loans in Germany. Becker et al. (2014) find strong evidence of the substitution from loans to bonds as a contraction in bank-credit supply at times that are characterized by tight lending standards, depressed aggregate lending and tight monetary policy.

Measuring the effects of macroprudential measures on banks' risk-taking and credit supply is far from trivial as there are many confounding factors, such as variation in bank lending due to changes in loan demand. First, there is the exogenous variation in capital requirements, which is not-observable and stagnant. Secondly, there are bank-specific requirements, not exogenous with respect to banks balance sheet. Third, it is important to disentangle credit supply from credit demand (Gropp, Mosk, Ongena, Wix (2019), Aiyar, Calomiris, and Wieladek (2014a and 2014b), Khwaja and Mian (2008) and Borio and Gambacorta (2017)). These challenges can be overcome by exploiting the three unique granular datasets (described in Section 2.2) and by relying on a robust econometric setup for identification (detailed in Section 3). The use of micro-data helps in addressing the confounding factors where the main dependent variable is specified as bank lending since this is the key transmission channel running from banks to the real economy (Buch and Goldberg (2017)). Aiyar, Calomiris, and Wieladek (2014a and 2014b) use employment growth rate and lending growth to each of the economic sectors as the dependent variable to control for credit demand. Also, the interaction of country and time fixed effects increases efficiency of the estimates, which allows controlling for changes in credit demand (Borio and Gambacorta (2017)). When measuring the effects on banks' lending from changes in policy measures which translate into higher capital requirements, it is important to control for bank characteristics, loan demand as well as country characteristics. Our empirical approach, following Borio and Gambacorta (2017) and Aiyar et al. (2014a and 2014b), controls for unemployment rate and includes lending growth to different economic sectors as the dependent variable, as well as country and time fixed effects (and the interaction of both), which increases efficiency of the estimates (Calonico et al. (2019) and Petterddon-Lidbon (2010)) and allows controlling for changes in credit demand. The panel with multi-country dimension allows having country and timing fixed effects, which absorb all possible variation related to country-level macroeconomic conditions.

The behavioural aspects of banking groups internal markets, have been greatly visited and largely theorised throughout the academic literature. Houston and James (1998) already studied the causal link between the conglomerate structures and lending, arguing that banks generate internal capital markets by distributing capital across subsidiaries, in an attempt to be more reactive to the local credit conditions, in their sought for new business opportunities. Campello (2002) and Cetorelli and Goldberg (2012) study the changes in the allocation of investments within the internal capital markets under different monetary policy shocks in the United States (US) banking sector. Campello (2002) follows Stein (1997) and Scharfstein and Stein (2000) in distinguishing between two different organizational structures, one in which a parent entity is entitled to centralise decisions, by allocating funding to some branches, and another one where the more efficient and profitable subsidiaries wind up subsidising the worse performing ones. This author then compares the loan-cash sensitivity under different monetary policy scenarios and concludes that US banks tend to engage in a more ”socialist” structure where investment is reallocated to the worse performing subsidiaries in the scenario assuming a tightening of rates by the US Federal Reserve Board. Cetorelli and Goldberg (2012) also study the internal lending under different monetary policy scenarios, and conclude that under a tighter monetary policy, the change in net liquidity flows from the parent to the international subsidiaries increases faster than it does under a looser and more accommodating policy strategy. Finally, Mili et al. (2017), study the adequacy of the subsidiaries' capital ratio given the parent entity fundamentals and capital regulation in the home country. Authors study regulatory differences in the jurisdiction of developed and developing countries and concluded that parent entities tend to increase the lending towards subsidiaries located in countries with a more robust legislation in detriment of subsidiaries operating under a less stringent capital regulation. In our empirical analysis, we study the effect of higher capital requirements on the internal allocation of intra-group resources, using disseminated data on equity and short and long-term debt.

In contrast to the hypothesis that moral hazard costs amplify risk-taking,[12] some literature suggests that regulatory surcharges had a positive disciplining effect. This is in line with some strands of the theoretical literature on the impact of capital based regulation on risk-taking. Having better capitalised banks, as a result of higher capital requirements, enhances financial stability by reducing bank risk-taking incentives and increasing banks' capital buffers against losses. Repullo (2004) finds that capital requirements can reduce banks' gambling incentives, leading to a “prudent equilibrium”. Cappelletti et al. (2019) find that banks subject to higher capital buffers reduced, in the short-term, credit supply to households and financial sectors and shifted lending to less risky counterparts within the non-financial corporations. The findings support the discussion on the short-run costs and provide policy-makers with relevant information to calibrate their policy actions. In terms of policy implications, as mentioned by Cappelletti et al. (2019), Hirtle, Kovner and Plosser (2019), Gersbach and Rochet (2017), and Repullo (2004), higher capital requirements could have

[12]The great financial crisis showed that certain institutions are too systemically important to fail, which may lead to misaligned incentives and greater moral hazard (ESRB (2015)). Shocks to these systemically important institutions may lead to losses and liquidity shortages in the financial system, both through direct and indirect channels.

potentially a positive disciplining effect by reducing risk-taking.

This paper contributes to the ongoing discussion about the macroprudential policy framework in the European context, in particular when assessing cross-border spillover effects induced by enacted or planned policy measures. The aims of the present paper are threefold. First, by using unique confidential databases with granular supervisory data and a robust econometric setup, we provide new insights for the scarce existing literature on the effects of higher capital buffer requirements on banking groups' lending and risk-taking. Second, we broaden the scope of the analysis beyond the bank lending and risk-taking, by assessing also the impact on banks' profitability. This allows for a better assessment of domestic and cross-border spillover effects of this macroprudential policy (OSII). Third, our paper relates to the literature on internal capital markets by harnessing the banking groups structure.

Our main results show that subsidiaries of banking groups whose parent has been identified as systemic, and subsequently constrained with a higher capital buffer (OSII), reduced credit supply and risk-taking towards non-financial corporations and marginally expanded lending supply towards households. This resulted into negative consequences to banks' profitability. Furthermore, our results indicate that parents cut down on holdings of both debt and equity issued by their subsidiaries, suggesting that banking banks engage in the restructuring of their internal financing and resources, when constrained with higher capital requirements.

The paper is structured as follows. Section 2 presents the data and describes the EBA framework for the identification of systemically important banks (OSII). Section 3 describes our empirical setup and demonstrates the robustness of our analysis. Section 4 provides the results, while Section 5 concludes.

2 Framework and data

2.1 OSII framework

In terms of OSII identification framework, under Article 131(3) of the Directive 2013/36/EU ('CRD IV'), the EBA Guidelines (EBA/GL/2014/10) established a two-step procedure for identifying OSII.[13] In the first step, the national authorities calculate a score for each relevant entity, at least at the highest level of consolidation of the banking group under their jurisdiction. The scoring process, established in the EBA guidelines, is based on four mandatory indicators that should capture the systemic footprint of each

[13] Although the EBA guidance is not compulsory, almost all countries follow these guidelines. Yet, the strict application of the EBA protocol might not properly reflect the specificities of the different countries, which may be relevant for the identification of the OSII.

Table 1: OSII scoring: Indicators and criterion (EBA guidelines, 2014)

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

institution (Table 1). A bank is then designated as OSII if its score is equal to or higher than 350 basis points. In order to account for the specificities of each EU member state's banking sector and the resulting statistical distribution of scores, relevant authorities may increase the threshold up to 425 basis points or decrease it to 275 basis points. This ensures the homogeneity of the group of OSII resulting from the automatic calculation. The second step of the procedure entails a supervisory overlay, whereby it is assessed whether further institutions are systemically relevant in order to be also qualified as OSII. To conduct the assessment, relevant authorities select the indicators considered adequate in capturing systemic risk in their domestic sector or in the economy of the EU.[14] Supervisory judgment is typically applied to identify institutions as OSII banks which fall under the automatic score.[15] From 1 January 2016, designated entities started to implement stricter capital requirements, typically in the form of CET1 capital buffers.[16] As the EBA guidelines do not provide any guidance on how the OSII buffer should be calibrated, EU countries have used various methods, and sometimes additional indicators, for the calibration of OSII buffers.[17] The EU legislation, however, provides some constrains: a cap limit of OSII of 2 percent, and for subsidiaries the additional capital requirement cannot exceed the higher between 1 percent and the global systemically important institutions (G-SII) or OSII buffer applicable to the group at the consolidated level.

[14]Moreover, according to the EBA guidelines, which are 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 banks' systemic importance.

[15]However, institutions with a score not exceeding 4.5 basis points should not be designated as OSII.

[16]In few countries (Estonia, the Netherlands and Slovakia) the OSII surcharge was complemented with the introduction of the systemic risk buffer.

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

As the calibration of the buffer, the timing of the introduction of the measure is also quite heterogeneous. There is considerable variation in the first year regarding the implementation of the policy measure, where several countries decided to defer the start of the execution of a positive OSII capital surcharge beyond 2016.[18] In addition, different multi-year linear phase-in periods have been adopted, with Estonia, Finland, Lithuania and Slovenia being the only countries that required fully loaded implementation already from the first year.

2.2 Data

In this section, we describe our primary data sources. We exploit the centralised European supervision setting by using:

(1) A quarterly confidential supervisory dataset, between 2014 Q4 and 2018 Q3, with 595 euro area banks, which includes both other systemically important banks (OSII 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 the common equity tier 1 (CET1) ratio or the total capital (TC) ratio. Out of the 595 entities in the sample, 274 had their ultimate parent identified as an OSII (corresponding to 38 parent banks being identified as OSII).

(2) A unique internal dataset on OSII banks, which includes for example the level of required capital buffer and the date of the OSII notification. Complementing confidential supervisory data with the information provided by national authorities allowed us to estimate the overall score of banks in the sample, from euro area countries, and calculate their distance from the threshold for the automatic identification as OSII.[19] With the data at hand, we identified 38 OSII ultimate parents, the vast majority of which qualifies as significant institutions (SI) with only 8 in the group of OSII qualifying as less significant institutions (LSIs).

(3) A quarterly confidential securities holding statistics (SHS) database, which collects data on a security-by-security basis and provides information on securities holdings by selected categories of euro area investors. Our focus lays mainly in three particular variables: short-term debt, long-term debt and equity held by parent banks within the same banking group. With the resources at hand, 25 distinct banking groups were matched, which allowed to collect information on the nominal value of securities held by parent banks within the same banking group.

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

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

These three unique datasets containing granular confidential data allowed us to implement an exclusive assessment of: i) the effects of higher capital buffers on banking groups' lending and risk-taking; and ii) the implications of higher capital requirements in the internal capital markets of banking groups.

To identify how banking groups adjust their balance sheets in response to higher capital buffer requirements, i.e. to estimate the causal impact of higher capital buffers on banking groups' credit supply and risk-taking behaviour, different indicators are considered. The exposure at default (EAD) is considered as a measure of total exposures.[20] To assess lending, the quarterly change in the natural logarithm of a bank credit volume is computed.[21] To measure both banks' profitability and risk-taking, the quarterly change in the return-on-assets (ROA) and in the risk-weights (or risk-weighted asset densities), respectively, are studied.[22] The average risk-weights, defined as the ratio of risk-weighted-assets to total exposures, is widely used to measure the average risk of exposures held by a bank. To assess the internal markets of banking groups, the quarterly change in the natural logarithm of the internal holdings of short and long-term debt and equity are considered. The internal markets are defined as the internal holdings of debt and equity taking place within a banking group structure. More precisely, we study the exchange of capital between the group's parent and its affiliated banks.

Table 2 reports the descriptive statistics of the sample for the dependent variables used in the empirical analysis across banks and portfolios, computed separately for banks below and above the threshold (which identifies banks as systemically important), as well as before and after the notification period. Some heterogeneity emerges when looking at the average lending growth and internal markets, in particular with the reduction in the credit granted, risk-taking and internal capital markets in banks above the threshold (used in the identification of banks as systemically important).

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

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

[22] For standard approach (STA) exposures the risk-weights are defined according to external ratings or level of collateralization, as detailed in the Regulation (EU) No 575/2013 ('CRR'). For internal ratings based approach (IRB) exposures the risk-weights are calculated according to Articles 153 and 154 of the CRR. This indicator is also used by the EBA in their annual review of RWA's variability (https://www.eba.europa.eu/-/eba-interim-report-on-the-consistency-of-risk-weighted-assets-in-the-banking-book).

Table 2: Descriptive statistics

	Banks below the threshold		Banks above the threshold	
	Pre-notification	Post-notification	Pre-notification	Post-notification
Panel A: Δ Log Credit				
Households	0.018	0.005	0.013	0.015
	(0.322)	(0.165)	(0.021)	(0.119)
Non-financial corporations	0.010	0.008	-0.016	-0.009
	(0.449)	(0.362)	(0.117)	(0.542)
Non-financial private sector	0.010	0.007	-0.001	0.001
	(0.321)	(0.220)	(0.029)	(0.363)
Financial sector	-0.030	0.001	-0.010	-0.008
	(0.669)	(0.632)	(0.265)	(0.336)
Public sector	0.068	0.030	0.077	0.015
	(0.639)	(0.440)	(0.343)	(0.445)
Panel B: Δ Avg. Risk-weights				
Households	-0.030	0.003	-0.004	-0.002
	(2.178)	(0.568)	(0.012)	(0.051)
Non-financial corporations	-0.001	0.004	0.004	0.043
	(1.868)	(2.779)	(0.011)	(2.074)
Non-financial private sector	-0.100	-0.0003	-0.003	-0.161
	(4.039)	(0.504)	(0.006)	(16.749)
Financial sector	1.503	-0.414	-0.011	-0.002
	(492.44)	(12.977)	(0.018)	(0.109)
Panel C: Δ Avg. Return-on-assets				
	-0.052	-0.001	0.013	-0.038
	(0.013)	(0.009)	(0.011)	(0.034)
Panel D: Δ Log Internal holdings				
Short-term debt	0.154	0.048	-0.010	0.058
	(0.053)	(0.065)	(1.465)	(1.773)
Long-term debt	-0.166	0.016	-0.020	-0.030
	(0.149)	(0.262)	(0.134)	(0.228)
Equity	-0.026	0.196	-0.119	0.331
	(0.054)	(2.440)	(0.891)	(2.007)

Notes: Data between 2014 Q4 and 2018 Q3. Mean values are computed separately for banks below and above the threshold, as well as before and after the notification of a bank as systemically important (OSII). Standard deviations are reported in parenthesis. Panel A reports the mean values for the quarterly change in the log credit volume per sector. Panel B shows the means values for the quarterly change in the risk-weights per sector. Panel C shows the average values for the quarterly change in the return-on-assets. Panel D reports the mean values for the quarterly change in the log of internal holdings of short and long-term debt and equity.

3 Econometric setup

This section presents the empirical strategy of the paper and is divided into two subsections. In the first subsection, the identification strategy is detailed. The second subsection presents the robustness checks to assess the validity of our results.

3.1 Identification strategy

The centralised supervision provides an excellent setting for empirical identification, allowing to exploit: (i) an unique database of systemically important banks (OSII) characteristics; (ii) a confidential supervisory dataset, which includes both other systemically important banks (OSII) and non-systemically important banks (non-OSII); and (iii) a confidential database on banks holdings on a security-by-security basis. These three unique datasets allowed us to implement an exclusive assessment of the effects of higher capital buffers on banking groups' lending and risk-taking and further implications in the internal capital markets. Also, following the OSII framework, the selection of OSII banks is implemented by using observable banks' characteristics, which allowed us to identify how banks adjust their balance sheets in response to higher capital buffers. The EBA scoring process induces for a randomized experiment in a neighborhood of the threshold. This policy design permits an implementation of both a fuzzy regression discontinuity and a difference-in-differences matching designs, which exploit both the regulatory change and the discontinuity induced by the OSII identification process. Estimating the impact of higher capital buffers on banking groups' lending and risk-taking behaviour poses a number of challenges. There is the exogenous variation in capital requirements, which is not-observable, where it is also relevant to disentangle credit supply from credit demand. These challenges can be overcome by exploiting the three granular datasets and by relying on our robust econometric setup. In our study, we rely on micro bank level data which helps in addressing the confounding factors, where the main dependent variable is specified as bank lending and risk-taking behaviour. We control for loan demand and country characteristics by using lending growth to different sectors as the dependent variable, which allows disentangling bank credit demand from supply (Aiyar et al. (2014a and 2014b)). Also, following Borio and Gambacorta (2017) and Aiyar et al. (2014a and 2014b), our empirical analysis controls for unemployment rate and includes both country and time fixed effects (and respective interaction of both), which increases efficiency of the estimates (Calonico et al. (2019) and Petterddon-Lidbon (2010)) and allows controlling for changes in credit demand.[23]

[23] A longitudinal dataset is used, with controls for both time and country fixed effects ($\eta_{t,c}$). The same models are also considered by adding a bank/time fixed effects and results do not change substantially.

3.1.1 Fuzzy regression discontinuity design

To identify a banking groups' response to higher capital buffers, as a result of the identification of a parent as systemically important, is challenging. Especially since the introduction of capital surcharges may be correlated with credit supply and risk-taking. Capital buffer requirements, for instance, reflect the actual and expected 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 probably subject to tighter capital restrictions.[24] To address these challenges, we rely on a feature of the OSII institutional framework, particularly the fact that the identification of the OSII and the application of the related capital buffer are determined by a predefined threshold. As covered in Section 2.1, the EBA guidelines on the identification of OSII establish a scoring process based on four mandatory indicators: size, importance, complexity/cross-border activity and interconnectedness. Taking into account these criteria, national authorities assign to each bank under their jurisdiction a score that should represent its systemic footprint within the national banking system. And most crucially, institutions with a score equal to or higher than a certain threshold are automatically identified as systemically important (OSII).

Although the automatic calculation has been complemented with supervisory judgment, the OSII framework provides a natural setting for a regression discontinuity design.[25] This strategy exploits both the policy change and the discontinuity induced by the OSII identification process. The key underlying assumption is that there exists a window around the threshold such that the assignment above or below the cutoff is probabilistic and the outcomes depend directly from the score.[26] The EBA assessment protocol induces a randomized experiment in the neighborhood 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 explain the identification strategy of this study, a setting where a sample of N banks is used, 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 parent bank is identified as OSII and $I_{i,t} = 0$

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

[25] These designs were first introduced in the evaluation literature by Thistlethwaite and Campbell (1960) and Lee and Lemieux (2010). Leonardi and Pica (2013) apply a difference-in-discontinuities approach to study the effect of employment protection legislation on wages. Grembi et al. (2016) investigate the impact of relaxing fiscal rules on a wide array of outcomes. Imbens (2008) use the regression discontinuity designs for evaluating causal effects of interventions, where assignment to a treatment is determined at least partly by the value of observed covariates lying on either side of a fixed threshold.

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

otherwise. Formally, the treatment assignment is given by:

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

where $S_{i,t}$ is the bank i's score used for the annual review of the OSII identification. $THOLD_{c(i),t}$ is the threshold based on which a parent bank is identified as an OSII. 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,[27] national authorities shall review annually the identification of OSII, 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.[28] In order to simplify, we refer to $THOLD_{c(i),t}$ as $THOLD$ and to $\tau_{c(i),t}$ as τ.

Since the objective of this empirical analysis is to study the effect of the identification $(I_{i,t})$ on affiliated 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:

$$Y_{i,t} = \begin{cases} Y_{i,t}(0) & \text{if } I_{i,t} = 0 \\ Y_{i,t}(1) & \text{otherwise.} \end{cases} \tag{2}$$

The start of the treatment corresponds to the date when the national authorities notified their decision to the European Central Bank (ECB).[29] 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 OSII and may be charged with an additional capital requirement. It should be noted that the introduction of the OSII 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 OSII. Therefore it is assumed the adjustment period to have started just after the notifications have been issued by the national authorities.

In order to estimate the average treatment effect on the treated (ATT) close to the threshold at the

[27] Article 131(3) of the Directive 2013/36/EU ('CRDIV').

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

[29] 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 OSII 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 OSII buffers, than the ones applied by the national authority.

inception, the cross-sectional nature of the data is exploited. If the identification is sharp, the point estimate can be obtained by the following regression model in an interval around the threshold. The expected value of the outcome variable on the left ($E[Y_i(0)|X_i = x]$) and on the right of the threshold ($E[Y_i(1)|X_i = x]$) can be approximated by a polynomial function of the score. In particular, following Cattaneo, Idrobo and Titiunik (2017a,b) a local polynomial estimator is used. We fit a regression equation using only observations near the threshold, separately for control and treatment units. In particular the observations between $c-h$ and $c+h'$ are used, where $h > 0$ and $h' > 0$ define the bandwidth which 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, in order to have a more precise estimate of the treatment effect at the cut-off.[30] Therefore, two local weighted regressions are estimated, respectively, for the observations above and below the threshold:

$$\mu_-(S^*_{i,t}) = E[Y_{i,t}(0)|X_{i,t} = x] = \mu_{-,0} + \mu_{-,1}S^*_{i,t} + \mu_{-,2}S^{*2}_{i,t} + ... + \mu_{-,p}S^{*p}_{i,t} \tag{3}$$

$$\mu_+(S^*_{i,t}) = E[Y_{i,t}(1)|X_{i,t} = x] = \mu_{+,0} + \mu_{+,1}S^*_{i,t} + \mu_{+,2}S^{*2}_{i,t} + ... + \mu_{+,p}S^{*p}_{i,t} \tag{4}$$

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 contemporaneous and lagged value of CET1 minus the associated capital requirement (i.e. the distance from the current and required CET1 ratio), contemporaneous and lagged value of the risk-weighted assets (in log terms) and the country's unemployment rate. 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.

For implementing the local polynomial approach there is a need to select the polynomial order and the weighting scheme. For the weighting scheme we use a triangular kernel function which assigns zero weight to all observations with score outside the interval $[c+h; c+h']$, and positive weights to all observations within this interval. The weight is maximized at the threshold, and declines symmetrically and linearly as the value of the score gets farther from the cutoff. Regarding the selection of the order of the polynomial, it is important to mention that 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 but also increases the variability of the treatment effect estimator and it can produce over-fitting of the data and lead to unreliable results near boundary points.[31] Combined, these factors have led us to prefer the local linear regression discontinuity estimator.[32]

[30] The weights are determined by a so-called kernel function.
[31] See Gelman and Imbens (2018) for the risk of selecting high-order polynomial.
[32] Pei et al, (2020) propose and test an order-selection procedure.

Regarding the bandwidth, we rely on a data-driven selection approach in order to avoid specification searching and ad-hoc decisions. Most bandwidth selection methods aim to balance the bias-variance trade-off. For example, a smaller bandwidth reduces the misspecification error of the local polynomial approximation, but simultaneously increases the variance of the estimated coefficients because fewer observations are available for estimation. The two most popular approaches (Imbens and Kalyanaraman (2012)) are used: i) the approach which seeks to minimize the mean squared error (MSE) of the local polynomial RD point estimator given a choice of the polynomial order and the weighting scheme[33]; and ii) the approach which aims to minimize an approximation to the coverage error (CER) of the confidence interval. Alternatively, a global polynomial approach can be pursued by estimating a high order polynomial[34] and considering all observations. In the application of the regression discontinuity design, under the assumptions of linear effect of the controls, the previous equation can be estimated as:

$$Y_{i,t} = \mu_{-,0}+\mu_{-,1}S^{*}_{i,t}+\mu_{-,2}S^{*2}_{i,t}+...+\mu_{-,p}S^{*p}_{i,t}+(\hat{\tau}_{TEAT}+\beta_{+,1}S^{*}_{i,t}+\beta_{+,2}S^{*2}_{i,t}+...+\beta_{+,p}S^{*p}_{i,t})I_{i,t}+\beta_3 X_{i,t}+\varepsilon_{i,t} \quad (5)$$

where $I_{i,t}$ is the dummy for parents identified as other systemically important institutions (OSII). $\hat{\tau}_{TEAT}$ is the treatment effect at the threshold point estimate and $X_{i,t}$ is a matrix containing control variables, which in our study correspond to the banks' voluntary capital buffer (CET1 minus requirements), the risk-weighted assets (in logs) and the country's unemployment rate.

When focusing on the short-run effects of higher capital buffers, a longitudinal dataset is used by controlling for time and country fixed effects and the interaction of both country and time fixed effects (let $\eta_{t,c}$ denote the vector of fixed effects). The inclusion of country and time fixed effects increases efficiency of the estimates (Calonico et al. (2019) and Petterddon-Lidbon (2010)).[35] Adding these fixed effects reflects also the rich nature of our panel data, which allows controlling for both changes in credit demand (Borio and Gambacorta (2017)) and macroeconomic factors (not bank characteristics) that are time invariant and affect the banking system in the same manner. The panel with multi-country dimension allows having country and timing fixed effects, which absorb all possible variation related to country-level macroeconomic conditions.

In the identification process of the OSII, national authorities consider some banks to be systemically relevant even if their score is below the $THOLD$. Consequently, expert supervisory judgment is applied by

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

[34]When using a high order polynomial Gelman and Imbens (2018) argue that estimators for causal effects based on such methods can be misleading, therefore recommending the use of estimators based on local linear or quadratic polynomials or other smooth functions.

[35]The same models are also considered by adding a bank/time-fixed effects and results do not change substantially.

the national authority.[36] This implies that the probability of being identified as OSII changes discontinuously at the threshold (Figure 2), leading to the application of a fuzzy regression discontinuity model:

$$\lim_{\varepsilon \to 0^+} \Pr\left(I_{i,t} = 1 \mid S_{i,t} = THOLD + \varepsilon,\ t \geqslant \tau\right) > \lim_{\varepsilon \to 0^-} \Pr\left(I_{i,t} = 0 \mid S_{i,\tau(t)} = THOLD + \varepsilon,\ t \geqslant \tau\right) \tag{6}$$

In this setup, it is possible to take advantage of the discontinuous change in the treatment assignment at the threshold to measure the causal impact of the treatment on the outcomes of interest. Following Hahn et al. (2001), let $Y^+ = \lim_{\varepsilon \to 0^+} E\left[Y_{i,t} \middle| \ S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$ and $Y^- = \lim_{\varepsilon \to 0^-} E\left[Y_{i,t} \middle| \ S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. The analogous expressions for the treatment status are $I^+ = \lim_{\varepsilon \to 0^+} E\left[I_{i,t} | S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$ and $I^- = \lim_{\varepsilon \to 0^-} E\left[I_{i,t} | S_{i,t} = S_c + \varepsilon,\ t \geqslant \tau_{c(i)}\right]$. In the standard regression discontinuity design setting the treatment effect is given by:

$$\pi_{FRD} = \frac{Y^+ - Y^-}{I^+ - I^-} \tag{7}$$

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

3.1.2 Difference-in-differences matching

The second part of our study focuses on determining the effect of higher capital requirements on the banking groups' internal markets (i.e. the intra-group lending and equity holding behaviour). A difference-in-differences design would be optimal for this policy evaluation setting. However, the (previously discussed) supervisory expert judgment for the OSII identification renders the capital constraints decisions to be non-random, and therefore causal inference on a difference-in-differences design alone would be considered spurious (Gropp et al. (2019)). To this purpose, the combination between the difference-in-differences design and the bias-corrected Abadie and Imbens (2011) matching estimator is used. This alternative identification strategy is employed, as opposed to the fuzzy regression discontinuity design above described in Section 3.1.1, in order to obtain a more robust inference, given the less populated intra-group holdings dataset. This estimation method minimizes the Mahalanobis distance between the covariates of banks whose parent has been identified as systemically important institution (OSII) and respective matches. The matching strategy aims at identifying three non-systemically important banks (non-OSII) to each parent and affiliated banks

[36] The identification process of the OSII is partly determined by factors other than the banks' score, because of national supervisory overlay. If the OSII assessment was 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.

(above the threshold) with equivalent characteristics by using a set of observable covariates, namely the banks' voluntary buffer (CET1 capital minus requirements), the risk-weighted assets (in log terms) and the country's unemployment rate. The matching framework with difference-in-differences approach is implemented by comparing the changes in in the variables of interest between pre-treatment and post-treatment periods across groups, by matching the treated banks (OSII) with a matching counterfactual observation constructed from similar untreated banks (non-OSII). This strategy matches banks of similar size and capital levels, therefore reducing the differences between treated and untreated banks which could compromise any inference. The treatment corresponds to the first notification period which occurs in 2015 Q4, and the analysis is focused on the quarters before and after the treatment, i.e. from 2014 Q4 to 2015 Q3 (pre-treatment period) and from 2016 Q1 to 2018 Q3 (post-treatment period). The estimates for the average treatment effects on the treated (ATT) is given by:

$$ATT_i = \frac{1}{N_{osii}} \sum_{i \in osii} (\Delta Y_i^{osii} - \sum_{j \in non-osii} w\ (i,j) \Delta Y_j^{non-osii}) \tag{8}$$

where ATT_i is the average treatment effect on the treated group in the outcome variables, namely the quarterly change in intra-group lending and equity holdings. N_{osii} is the sub-sample of treated banks (i.e. whose parent has been identified as an OSII). ΔY_i^{osii} and $\Delta Y_i^{non-osii}$ represent the change in outcome between the pre-treatment and post-treatment periods for treated and untreated banks (systemically important and non-systemically important banks), respectively. Treated bank i are matched to a counterfactual observation that is a weighted average (weighted by $w\ (i,j)$) of j observations in the control group. The Mahalanobis distance is used, in which the weights $w\ (i,j)$ are based on the inverse of the covariates' variance–covariance matrix. In this way, we identify an adequate control group (non-systemically important banks) using the Mahalanobis distance that determines similarity between banks by a weighted function of observable covariates for each bank.

The difference-in-differences matching refers to the combination of the difference-in-differences framework (ΔY_i^{osii} - $\Delta Y_i^{non-osii}$) and the bias-corrected matching estimator by Abadie and Imbens (2011) that uses the most similar banks in the control group to construct a matching counterfactual ($w\ (i,j) \Delta Y_j^{non-osii}$).

3.2 Validation of the empirical strategy

3.2.1 Fuzzy regression discontinuity design

The key assumption for casually identifying the effect of higher capital requirements on banking groups' lending and risk-taking, as a result of the identification of a bank as systemically important, is that banks do not actively try to change or "manipulate" their scores and thus their identification as systemically important (OSII). Since the OSII score depends on each banks' characteristics, on the whole national banking system, as well as on the expert judgment of the national authority, it is unlikely that each bank could "manipulate" its probability of being identified as an OSII. For example, banks can aim to reduce total assets via deleveraging, although the overall sub-scores also depend on the behaviour of other banks in a certain country. In order to validate this assumption, different tests were performed. First, the distribution of the scores around the threshold was analysed to check if the number of observations below the cutoff is considerably different from the number of observations above it. To perform this test, the procedure of McCrary (2008) is followed where the continuity at the cutoff of the score density is assessed. Figure 1 (left panel), in the Appendix, plots the density of the normalised scores and does not reveal any evidence of manipulation in the density at the threshold, which reassures the absence of manipulative sorting. In addition, the test proposed by Cattaneo, Jansson and Ma (2015a) is followed, where a local polynomial density estimator is used and does not require binning the data. To construct this test, a polynomial of order 1 is used. The resulting p-value equals to 0.24, which is insufficient to reject the hypothesis of a non-significant jump around the threshold, therefore supporting the assumption of absence of a manipulative sorting. Figure 1 (right panel) presents the graphical representation.

Another important falsification test involves examining whether systemically important banks (OSII) near the cutoff are similar to other non-systemically important banks (non-OSII). The intuition is straightforward, if banks lack of the ability to manipulate the value of the score received then they should be similar, just above and below the cutoff, in all those characteristics that could not have been affected by the treatment. In particular, predetermined covariates (in our study, CET1 voluntary buffer, risk-weighted assets and country's unemployment rate) should be similar across treated and untreated banks. For this purpose, the continuity of the covariates in the neighbourhood of the threshold is tested. Table 10 and Figure 9 show that there is no significant evidence of the existence of a discontinuity between the covariates of both treated and untreated groups (with non-significant jumps).[37] These results are encouraging as they provide evidence of the absence of non-random sorting by banks close to the threshold, therefore allowing for a randomized experiment.

[37] Note that the more notorious jump in the risk-weighted assets is given by the sparsity of this specific variable across banks.

Finally, to ensure that our results are robust and independent of the selected bandwidths, a comparison of multiple fuzzy regression discontinuity design estimates are provided, where different combinations of bandwidths are allowed at both sides of the threshold. Results are consistent for the different combinations of bandwidths, thus attesting the robustness of our results (Table 11).

3.2.2 Difference-in-differences matching design

To assess the implications of higher capital requirements in the internal capital markets of banking groups a difference-in-differences matching design was used.[38] It is necessary to ensure that treated and untreated banks are grouped in compliance with the ”balancing property hypothesis” to have identical distributions for all baseline variables in both groups. Therefore, to validate the results of this approach, we test for the ”balancing property hypothesis” developed by Rosenbaum and Rubin (1983) and the existence of a common trend in the pre-treatment period. The balancing hypothesis ensures that banks' characteristics follow the same distribution, independently of their treatment status. The test is conducted by splitting the sample into a number of blocks that ensures that the mean propensity score is not different for both treated and untreated banks in each block, theoretically meaning that there is a random access to the treatment. This test is implemented by using as matching covariates the voluntary buffer (CET1 capital level minus requirements), the risk-weighted assets (in log terms) and the country's unemployment rate. Figure 10, in the Appendix, shows that the algorithm splits the sample in 5 blocks for which the mean of each covariate does not differ among treated and untreated banks. Results support the suitability of the selected covariates to perform the matching. This test also confirms the “no unmeasured confounders” assumption that all variables that affect treatment assignment and outcome have been measured.

At the same time, the existence of parallel trends prior to the treatment is a critical assumption to ensure internal validity of this approach. This test is constructed following the methodology of Cerulli and Ventura (2019), which estimates the dynamic regression,

$$Y_{i,t} = \mu_{i,j} + \lambda X_{i,t} + \beta_{t+2} D_{i,t+2} + \beta_{t+1} D_{i,t+1} + \beta_t D_{i,t} + \beta_{t-1} D_{i,t-1} + \beta_{t-2} D_{i,t-2} + \varepsilon_{i,t} \tag{9}$$

where $Y_{i,t}$ is the outcome variable of interest, $\mu_{i,j}$ represents the fixed effects, $D_{i,t}$ is the binary systemically important bank identification (OSII) and $X_{i,t}$ is a matrix containing the matching covariates: voluntary buffer (CET1 capital level minus requirements), risk-weighted assets (in log terms) and the country's unem-

[38]This strategy was implemented, as opposed to the fuzzy regression discontinuity design, in order to obtain a more robust inference, given the less populated intra-group holdings dataset.

ployment rate. The coefficients for the leads β_{t+2} and β_{t+1} are jointly tested for significance.

If the test fails to reject the null hypothesis that the leads β_{t+2} and β_{t+1} are statistically equal to zero, i.e. it is statistically not significant, then the parallel trend is expected to hold. Results in Table 13 show that the test fails to reject the null hypothesis of the lead coefficients being statistically equal to zero. It is assumed that $Y_{i,t}$ is determined by the contemporaneous and lagged values of the treatment, and hence the necessary condition for the existence of parallel pre-treatment trends holds.

4 Results

The probability of a bank being designated as systemically important (OSII) increases significantly and discontinuously if it receives a score above the automatic cutoff (Figure 2 in the Appendix). Not surprisingly, the percentage of banks on the right of the threshold that are designated as OSII is almost equal to one, as these banks should be automatically qualified as systemically important. By contrast, several institutions below the cutoff are, nevertheless, designated as OSII because of the supervisory judgment.[39] Therefore, the use of both the fuzzy regression discontinuity and the difference-in-differences matching designs are appropriate for the setting at hand. The fuzzy regression discontinuity design estimates from our baseline specification are reported in Section 4.1, from Tables 3 to 8, which respectively present the results for lending, risk-taking and profitability. The difference-in-differences matching design[40] results on the internal capital markets of banking groups are reported in Section 4.2 Table 9.

4.1 Impact of higher capital buffers on banking groups' lending and risk-taking

The tables below report the estimates from our baseline specification, namely the fuzzy regression discontinuity design, which assesses the European affiliated banks' behaviour on lending, risk-taking and profitability, when the respective parent has been identified as systemically important and constrained with a capital buffer (OSII). The dependent variable for lending, in Tables 3 and 6, is the quarterly change in the log credit volume. The risk-taking, in Tables 4 and 7, is the quarterly change in the average risk-weights or risk-weighted assets density. Finally, the dependent variable for profitability, in Tables 5 and 8, is the quarterly change in profits measured in terms of the return-on-assets (ROA). Data for lending and risk-taking

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

[40]This alternative identification strategy is used, instead of the fuzzy regression discontinuity design in order to obtain a more robust inference, given the less populated intra-group holdings dataset.

is aggregated into different categories - households, non-financial corporations, non-financial private sector, financial sector and public sector (for lending only)[41] - so as to identify the effect of the regulatory surcharge on each sector of the economy.[42]

4.1.1 All subsidiaries (domestic and cross-border)

The estimates for all the affiliated banks' behaviour on lending, risk-taking and profitability, when the respective parent has been identified as systemically important and constrained with a capital buffer (OSII), are described in Tables 3, 4 and 5. The results presented below are for all European domestic and cross-border subsidiaries of banking groups.

Table 3: Lending: Average effect of the OSII buffer (all subsidiaries: domestic and cross-border)

	Households	Non-financial corporations	Non-financial private sector	Financial sector	Public sector
Δ Log Credit					
MSE-optimal bandwidth	0.028**	-0.058*	0.023	-0.039	0.081
	(0.017)	(0.096)	(0.238)	(0.178)	(0.239)
Bandwidth	[190,400]	[233,1520]	[264,592]	[307,1086]	[221,1214]
Observations	509	820	555	455	780
CER-optimal bandwidth	0.034**	-0.059	0.039	-0.069	0.066
	(0.044)	(0.140)	(0.186)	(0.233)	(0.488)
Bandwidth	[253,533]	[312,2033]	[353,793]	[408,1442]	[296,1624]
Observations	509	820	555	455	780

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' lending. The dependent variable is the quarterly change in the log credit volume. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2$^{\text{nd}}$ and 98$^{\text{th}}$ percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

[41] Since assets issued by governments or public entities are considered as safe assets, the risk-weights should be approximately equal to zero.

[42] Using loan growth to different sectors as the dependent variable allows disentangling bank credit demand from supply (Aiyar, Calomiris, and Wieladek, 2014a and 2014b).

Table 4: Risk-taking: Average effect of the OSII buffer (all subsidiaries: domestic and cross-border)

	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ Avg. Risk-weights				
MSE-optimal bandwidth	-0.009***	-0.017***	-0.023***	-0.012
	(0.001)	(0.000)	(0.000)	(0.287)
Bandwidth	[276,1102]	[304,1812]	[272,799]	[376,1933]
Observations	658	844	646	532
CER-optimal bandwidth	-0.012***	-0.023***	-0.027***	-0.009
	(0.002)	(0.000)	(0.001)	(0.424)
Bandwidth	[207,826]	[227,1354]	[204,597]	[283,1455]
Observations	658	844	646	532

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' risk-taking. The dependent variable is the quarterly change in the average risk-weights. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 5: Profitability: Average effect of the OSII buffer (all subsidiaries: domestic and cross-border)

ΔAvg. Return-on-assets	
MSE-optimal bandwidth	-0.001*
	(0.075)
Bandwidth	[348,1815]
Observations	516
CER-optimal bandwidth	-0.001*
	(0.086)
Bandwidth	[242,274]
Observations	516

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' profitability. The dependent variable is the quarterly change in the return-on-assets. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Results show that affiliated banks', when considering the entire sample of domestic and cross-border subsidiaries[43] whose respective parent has been identified as systemically important and constrained with a capital buffer (OSII), reduced their lending and also shifted their credit to less risky counterparts in the non-financial corporations sector. At the same time, results show the lending supply expansion towards marginally less risky loans in the households sector (Tables 3 and 4). Quantitatively, the estimates reported in Table 4 imply that banks just above the threshold reduced their average risk-taking on the non-financial corporations sector by approximately 0.02 percentage points more than banks just below the cutoff, after being identified as OSII. In order to address the possible banks' optimisation of IRB risk-weights (i.e. risk measurement manipulation), we have also studied one more specification by considering only portfolios subject to the standard approach (STA) risk-weights. Thus, if focusing only on STA risk-weights, our previous results are confirmed, with a significant (in statistical or economic terms) estimated coefficient for the reduction of risk-taking towards non-financial corporations (Table 12). Our estimates also show a decrease in affiliated banks' profitability (Table 5), which could be explained by the reduction in both credit supply and riskier loans, in particular in the non-financial corporations sector (safer assets generally result in lower returns). Figures 3, 4 and 5, in the Appendix, show a scatter-plot with the value of each dependent variable against the normalized score ($S^*_{i,t}$),[44] for banks in the neighborhood of the threshold.

4.1.2 Cross-border subsidiaries

For this part of the analysis, our sample is restricted to cross-border subsidiaries of banking groups. The estimates for the fuzzy regression discontinuity design focused on cross-border subsidiaries are reported in Tables 6, Table 7 and Table 8, which present the results for credit supply, risk-taking and profitability, respectively. Data is aggregated into five sectors as described in Section 4.1.1.

Results on banks' cross-border subsidiaries suggest potential spillover effects from more stringent capital requirements on the parent entity. Our estimates show that cross-border affiliated banks, whose respective parent has been identified as systemically important and constrained with a capital buffer (OSII), shifted their lending to less risky counterparts in the non-financial private sector. Moreover, there is a shift in the risk-taking towards households (Tables 6 and 7). At the same time, results also show that lending to financial entities decreases and to public sector increases (Table 6). Also, there is a decrease in affiliated

[43]Comprised of all the cross-border and domestic institutions in our sample.

[44]In order to have a comparable measure across banks, the distance of each banks' score relative to the threshold used by the relevant national authority is considered.

Table 6: Lending: Average effect of the OSII buffer (cross-border subsidiaries)

	Households	Non-financial corporations	Non-financial private sector	Financial sector	Public sector
Δ Log Credit					
MSE-optimal bandwidth	0.040	-0.091	-0.048	-0.078***	0.260*
	(0.235)	(0.421)	(0.673)	(0.004)	(0.057)
Bandwidth	[735,1486]	[743,1305]	[777,916]	[765,1669]	[794,862]
Observations	127	122	105	125	95
CER-optimal bandwidth	0.029**	-0.086	0.039	-0.14***	0.28*
	(0.279)	(0.442)	(0.7060)	(0.008)	(0.068)
Bandwidth	[592,1197]	[592,1040]	[619,729]	[610,1330]	[633,688]
Observations	127	122	105	125	95

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' lending. The dependent variable is the quarterly change in the log credit volume. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 7: Risk-taking: Average effect of the OSII buffer (cross-border subsidiaries)

	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ Avg. Risk-weights				
MSE-optimal bandwidth	0.053***	-0.007	-0.053*	-0.054
	(0.000)	(0.223)	(0.073)	(0.832)
Bandwidth	[752,1614]	[612,1706]	[808,827]	[666,1291]
Observations	111	137	70	109
CER-optimal bandwidth	0.049***	-0.009	-0.061*	-0.049
	(0.000)	(0.198)	(0.085)	(0.846)
Bandwidth	[606,1300]	[488,1360]	[644,659]	[531,1029]
Observations	111	137	70	109

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' risk-taking. The dependent variable is the quarterly change in the average risk-weights. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 8: Profitability: Average effect of the OSII buffer (cross-border subsidiaries)

ΔAvg. Return-on-assets	
MSE-optimal bandwidth	-0.003
	(0.816)
Bandwidth	[832,854]
Observations	73
CER-optimal bandwidth	-0.005
	(0.119)
Bandwidth	[666,694]
Observations	72

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' profitability. The dependent variable is the quarterly change in the return-on-assets. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

banks' profitability (Table 8), yet not significant, which could be explained by the increase in the risk-taking to households. These results suggest the idea of a shift in lending and risk-taking towards safer assets. Note that the results are robust to changes in the bandwidth selection. This indicates that national decisions by supervisory regulators potentially entail cross-border repercussions which may alter third-countries financial conditions and ultimately generate frictions in the real economy. Figures 6, 7 and 8, in the Appendix, show a scatter-plot with the value of each dependent variable against the normalized score ($S^*_{i,t}$), for banks in the neighborhood of the threshold.

Overall, results for both domestic and cross-border subsidiaries or for only cross-border subsidiaries are broadly aligned, i.e. affiliated banks, whose parent has been identified as systemically important and constrained with a higher capital buffer (OSII), reduced credit supply and risk-taking, in particular towards non-financial corporations. Results also show the lending supply expansion towards the households sector. At the same time, results show a reduction in affiliated banks' profitability explained by the banks' re-balancing behaviour for lending and risk-taking.

4.2 Impact of higher capital buffers banking groups internal markets

At the same time, the estimates from the difference-in-differences matching design also suggest a change in the holding and lending dynamics within the banks' internal structure. Table 9 reports the results from the difference-in-differences matching design, which assesses the European banking group reaction on their internal capital markets, when the parent has been identified as systemically important and constrained with a capital buffer (OSII). The dependent variables are the quarterly change in the natural logarithm of the internal holdings of short and long-term debt and equity. The internal capital markets are defined as the internal holdings of debt and equity taking place within a banking group. The treatment corresponds to the first notification period which occurs in 2015 Q4, and the analysis is focused on the quarters before and after the treatment, i.e. from 2014 Q4 to 2015 Q3 (pre-treatment period) and from 2016 Q1 to 2018 Q3 (post-treatment period). The table below presents the estimates for the average treatment effect on treated (ATT), which uses the Abadie and Imbens (2011) matching estimator along with the corresponding p-values.

Table 9: Internal capital markets: Average effect of the OSII buffer requirement

	Short-term debt	Long-term debt	Equity
ATT	-0.095**	-0.023**	-0.071***
	(0.045)	(0.011)	(0.003)
Number of matches	1:3	1:3	1:3
Observations	112	194	129

Notes: The table contains the estimate for the average treatment effect on treated (ATT) based on the bias-corrected Abadie and Imbens (2011) matching estimator. The dependent variables are the quarterly change in the natural logarithm of the intra-group short and long-term debt and shares holdings between parent bank and subsidiaries. Matching covariates include the country's unemployment rate, the banks' voluntary buffer (CET1 minus requirements) and the risk-weighted assets (in log terms). The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Bias-adjusted robust standard errors. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Results indicate that on average parent banks, just above the threshold and identified as systemically important (OSII), deleverage both the debt and equity holdings issued by their subsidiaries. Therefore, when parent banks are subject to higher capital buffers, there is a restructure of the internal financing and resources within the banking groups, which translates in parents cutting down their funding (in terms of liquidity) to their subsidiaries.

The validation tests, described in Section 3.2, show the stability of both the fuzzy regression discontinuity design and the difference-in-differences matching results. The procedure of McCrary (2008) and the test proposed by Cattaneo, Jansson and Ma (2015a) support the assumption of absence of a manipulative sorting (Figure 1). There is no significant evidence of the existence of a discontinuity between the covariates of both treated and untreated groups. Results provide evidence of the absence of non-random sorting by banks close to the threshold, therefore allowing for a randomized experiment (Figure 1 and Table 10). Also, the different combinations of bandwidths showed consistent estimates, thus attesting the robustness of our results (Table 11). To validate the results of the difference-in-differences matching design both the ”balancing property hypothesis” developed by Rosenbaum and Rubin (1983) and the existence of a common trend in the pre-treatment period (Cerulli and Ventura (2019)) were tested. Results support the suitability of the selected covariates to perform the matching and confirm the “no unmeasured confounders” assumption that all variables that affect treatment assignment and outcome have been measured (Figure 10). Also, the existence of a common trend in the pre-treatment period is confirmed (Table 13). All in all, the econometric setup fits well and results are stable.

5 Conclusions

The financial crisis emphasised the limitations of the supervisory framework in safeguarding the resilience of the banking system to adverse macro-financial shocks. In the euro area this led to changes in the supervisory institutional setting by moving to a centralised banking supervision, which included a higher scrutiny of the banking system. At the same time, besides the microprudential supervision, the EU built up the macroprudential policy toolkit to address risks of a systemic nature.[45] In this paper, we study the other systemically important institutions buffer (OSII) that aims to reduce the systemic risks to financial stability due to misaligned incentives and moral hazard of “too big to fail” institutions, which might benefit from implicit government guarantees. This macroprudential policy can generate unintended cross-border spillovers, both owing to regulatory arbitrage and risk management decisions taken by banking groups. Banking groups that rely on subsidiaries to operate across countries might restructure their internal capital markets or negatively reduce the local supply of credit. Since supervisory measures are expressed in ratios, banking groups can to a certain extent accommodate such higher capital buffer requirements, for example, by reducing lending locally or reallocating it to portfolios with lower risk, thus freeing up capital at the consolidated level.

In this paper, we explicitly analyse leakages of macroprudential policy measures. We study the impact of higher capital buffers, namely of OSII, on banking groups’ lending and risk-taking decisions and its further implications on the groups’ internal capital markets. The centralised supervision provides an excellent setting for empirical identification, allowing to exploit: (i) an unique database of systemically important banks (OSII) characteristics; (ii) a confidential supervisory dataset, which includes both other systemically important banks (OSII) and non-systemically important banks (non-OSII); and (iii) a confidential database

[45] National authorities and the ECB can deploy pre-emptive macroprudential tools to mitigate risk-taking and enhance the resilience of the financial system, while the ESRB can issue warnings and recommendations. At the same time, from a financial stability perspective, it was also important to mitigate a potential increase of banks’ risk-taking due to monetary policy easing.

on banks holdings on a security-by-security basis. For identification, we exploit the provision of the EBA framework on the criteria for the identification of systemically important institutions (OSII),[46] which relies on a two-step procedure:[47] i) a scoring process, which automatically qualifies a bank, with a score above a predetermined threshold, as systemically important; and ii) a supervisory expert judgement, which may qualify some banks below the threshold as systemically important. The EBA scoring process induces for a randomized experiment in a neighborhood of the threshold, therefore allowing to identify the effect of higher capital requirements by comparing the change in the outcome of interest of banks just above and below the cutoff, before and after the introduction of the additional surcharge. This policy design allows us to implement an exclusive assessment relying on both a fuzzy regression discontinuity and a difference-in-differences matching designs, which exploit both the regulatory change and the discontinuity induced by the OSII identification process. The fuzzy regression discontinuity design is the econometric setup to assess the effects of higher capital buffers on banking groups' lending and risk-taking and the difference-in-differences matching[48] is used to assess the implications of higher capital requirements in the internal capital markets of banking groups.

In our study we establish two main findings.

First, affiliated banks whose parent has been identified as systemically important and constrained with a higher capital buffer (OSII) reduced credit supply and risk-taking towards non-financial corporations and marginally expanded lending supply towards households. Results for both domestic and cross-border subsidiaries or for cross-border subsidiaries only are broadly aligned. At the same time, results show a reduction in affiliated banks' profitability explained by the banks' re-balancing behaviour for lending and risk-taking, i.e. risk adverse position and credit shifting towards safer options.

Second, lending and holding dynamics within banking groups are affected when a parent bank is identified as systemically important (OSII). Results indicate that on average parent banks, just above the threshold and identified as systemically important (OSII), deleverage holdings of both debt and equity issued by their subsidiaries. This suggests that, when parent banks are constrained with higher capital buffers, there is a restructure of the internal financing in banking groups, originated from parents cutting down their holdings within the internal capital markets with their subsidiaries.

[46]Under Article 131(3) of the Directive 2013/36/EU ('CRD IV') and the EBA Guidelines (EBA/GL/2014/10).

[47]A bank is designated as OSII if the score is equal or higher than 350 basis points. In order to account for the specificities of each EU member state's banking sector and the resulting statistical distribution of scores, relevant authorities may raise the threshold up to 425 basis points or decrease it to 275 basis points. This ensures the homogeneity of the group of OSII resulting from the automatic calculation. The two-step procedure allows banks that might not score above the 350 bps threshold to still be identified as OSII due to supervisory overlay.

[48]This alternative identification strategy is used, as opposed to the fuzzy regression discontinuity design in order to obtain a more robust inference, given the less populated intra-group holdings dataset.

In terms of financial stability implications, our results suggest that the implementation of higher capital requirements at the consolidated level leads to a reduction in lending and risk-taking in the local credit markets, particularly towards non-financial corporations. We observe that this macroprudential policy, aimed at strengthening the resilience of banks, can also trigger an adverse effect in the real economy (as suggested also by Admati et al. (2015) and Cappelletti et al. (2019)).[49] Also, our results follow the existent literature on the behaviour of the banking groups' internal markets (Campello (2002), Cetorelli and Goldberg (2012), Mili et al. (2017) and Buch and Goldberg (2017)) where banking groups react to a more stringent requirements by cutting down liquidity towards domestic and cross-border subsidiaries, therefore concentrating it around the parent. At the same time, as cited by Cappelletti et al. (2019), Gersbach and Rochet (2017)[50] and Repullo (2004), higher capital requirements can reduce banks' gambling incentives, leading to a "prudent equilibrium". Our findings contribute to this debate suggesting that higher capital buffer requirements have a positive disciplining effect by reducing banks' risk-taking, while having at the same time an adverse impact on the real economy via reduction of of affiliated banks' lending supply to non-financial corporations and consequent profitability of banks. Thus in terms of policy action, as suggested by Hanson et al. (2011) and Gropp et al. (2019), targeting the absolute amount of new capital to be raised[51] instead of the capital ratio could mitigate the temporary adverse impact in the real economy, along with the potential optimisation of the risk-weighted-assets. optimisation of the risk-weighted-assets. Also, cross-border spillover effects should be factored in when assessing and calibrating macroprudential policy measures to ensure the effectiveness and consistency of macroprudential policy. It is essential that policymakers coordinate potential cross-border effects in the policy measures adopted by national authorities, in order to adopt suitable reciprocating macroprudential measures. This follows Beck and Wagner (2016) and Colliard (2020) where they discuss the benefits of coordinating prudential supervision beyond national borders in order to internalise cross-border externalities.

[49] Banks tend to comply with higher capital requirements by dampening down their risk-weighted-assets, i.e. by deleveraging lending and risk-taking. Banks can increase capital ratios by: increasing capital (the numerator of the capital ratio) or by decreasing risk-weighted-assets (the denominator of the capital ratio) (Gropp et al. (2019)).

[50] Authors show that imposing stricter capital requirement in good states corrects capital misallocation, increases expected output and social welfare.

[51] As applied in the U.S. stress-tests conducted in 2009 (Hirtle et al. (2009)).

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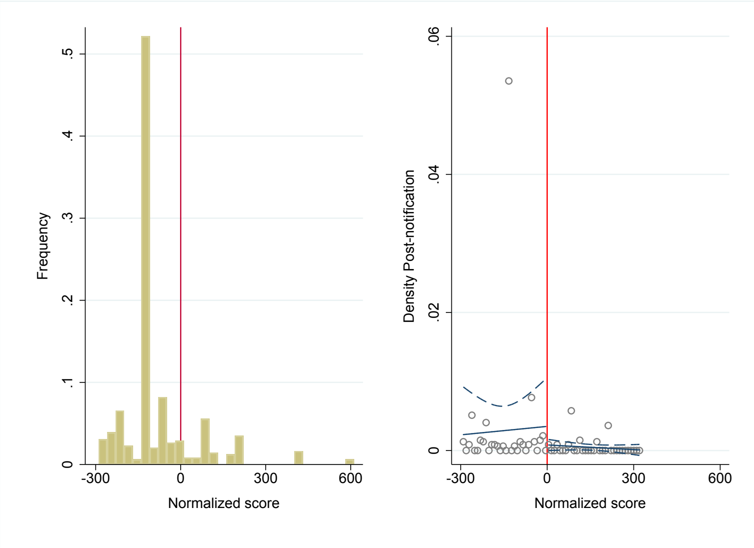
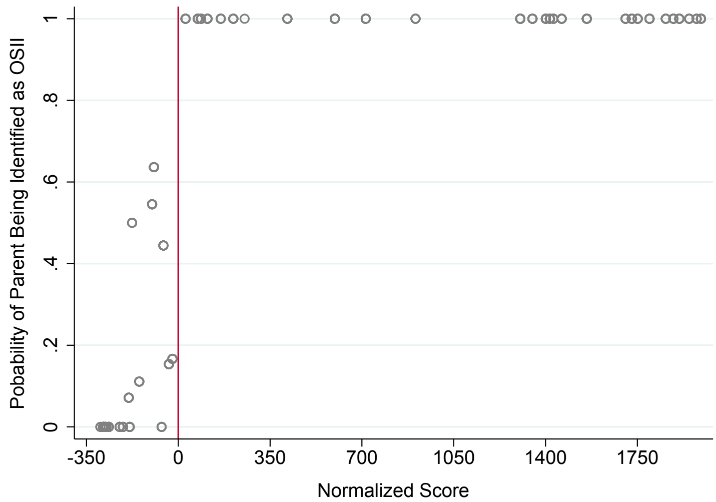
6 Appendix

Figure 1: McCrary's manipulation test of the running variable



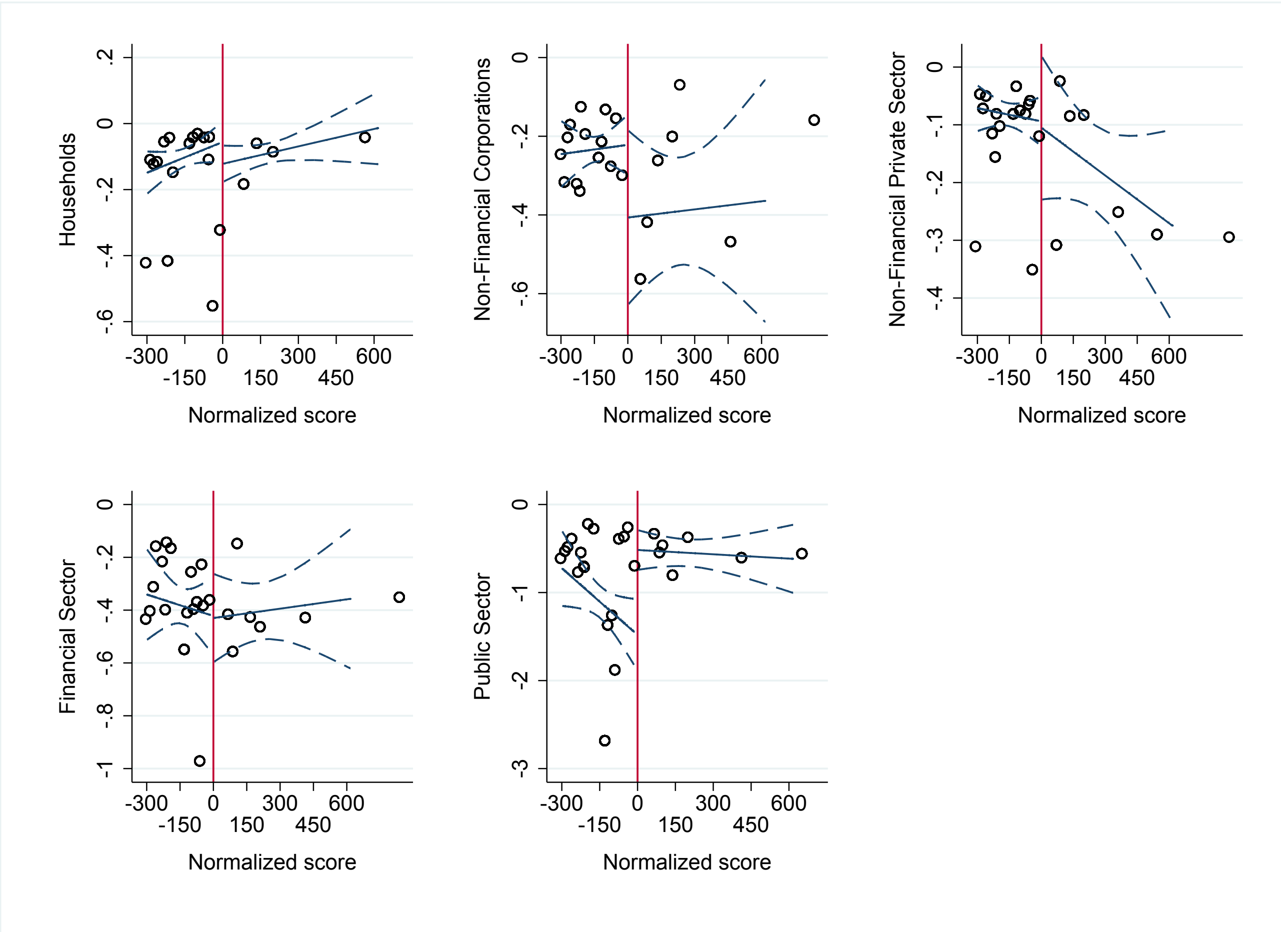
Notes: McCrary's test (McCrary, 2008) where the continuity at the cutoff of the score density is assessed. The right hand side figure plots the density of the normalized scores. The vertical axis shows the frequency of the parents' scores and the horizontal axis measures the score distance from the threshold. The left-hand side plot shows the McCrary test of density continuity. The central line plots fitted values of the regression of the parent score on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval. None of the plots provide sufficient significant visual evidence of systematic manipulation of the running variable.

Figure 2: Probability of being identified as OSII as a function of the score



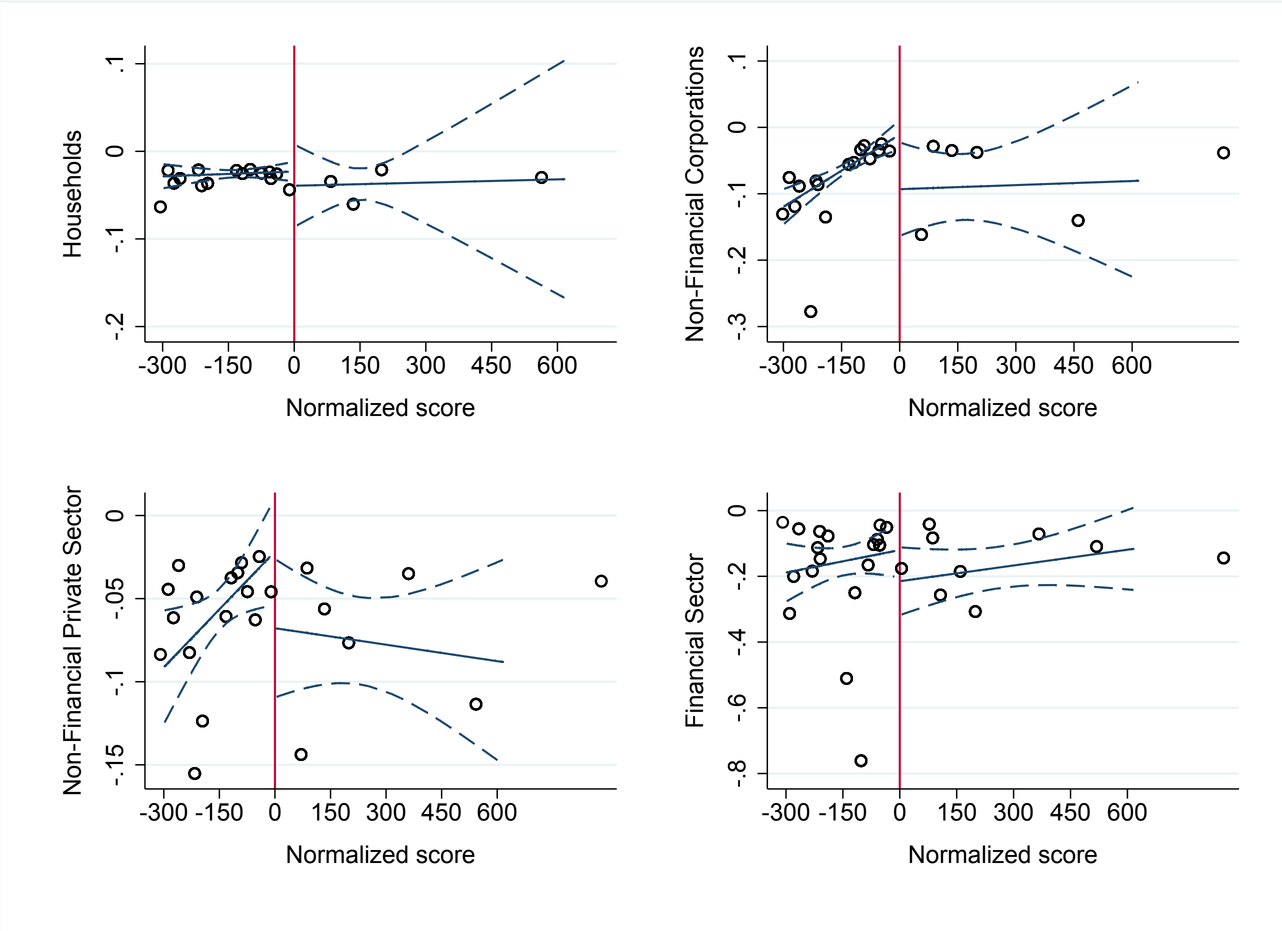
Notes: This figure represents the relationship of the parent score and respective identification as OSII. The vertical axis displays the number of parent banks identified as OSII while the horizontal axis measures the score relative to the threshold.

Figure 3: Lending: Average effect of the OSII buffer (all subsidiaries: domestic and cross-border)



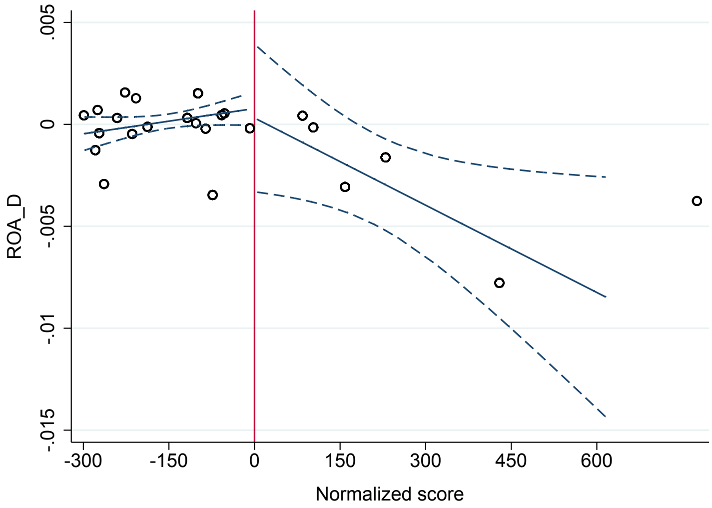
Notes: Regression discontinuity design graph for the quarterly credit growth (difference of log credit) for all subsidiaries. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values. The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 4: Risk-taking: Average effect of the OSII buffer (all subsidiaries: domestic and cross-border)



Notes: Regression discontinuity design graph for the quarterly change in the risk-weights for all subsidiaries. The data is trimmed at the 2nd and 98th percentiles to reduce the influence of extreme values. The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 5: Profitability: Average effect of the OSII buffer (all subsidiaries: domestic and cross-border)



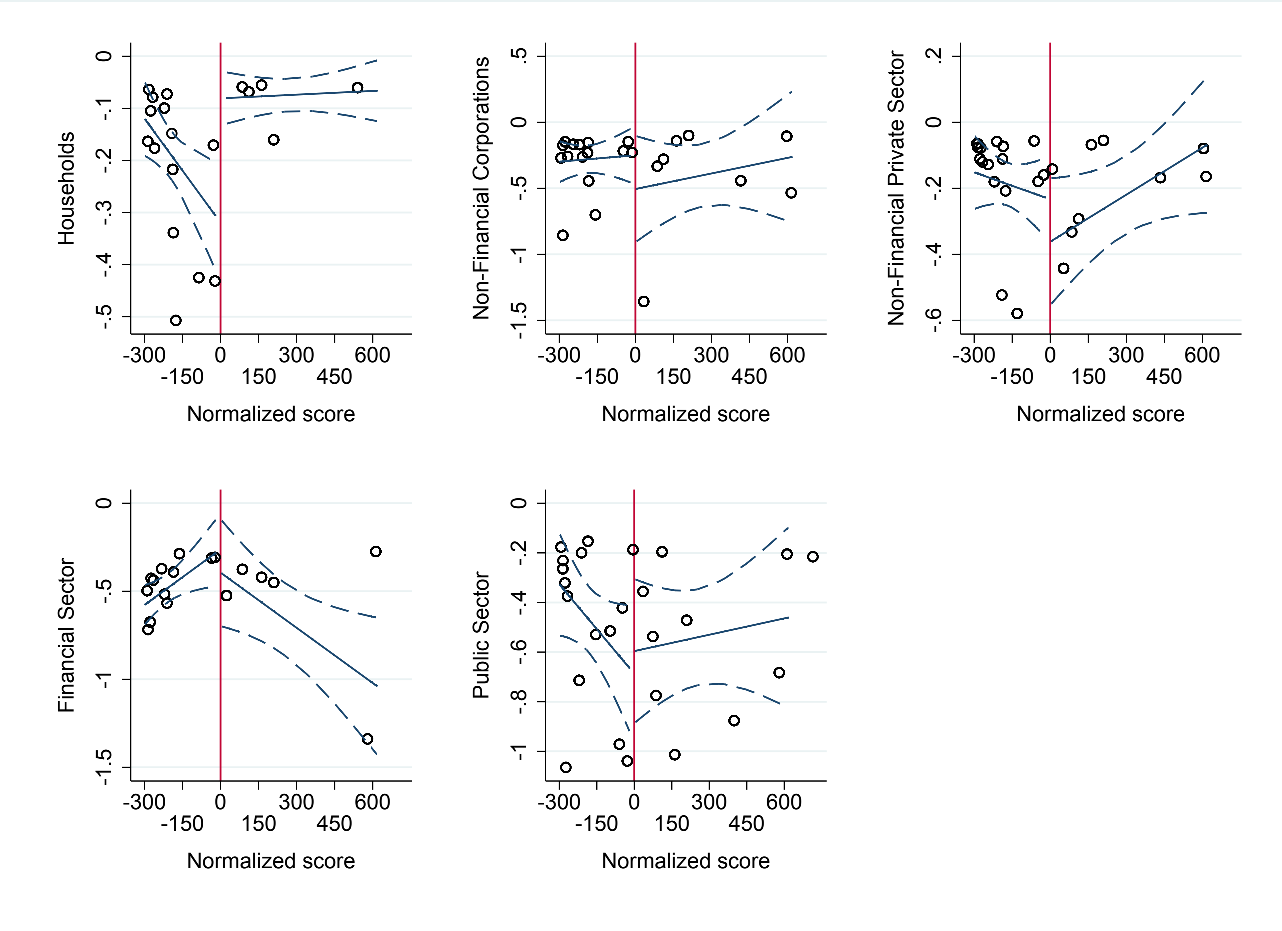
Notes: Regression discontinuity design graph for the quarterly change in profitability (ROA) for all subsidiaries. The data is trimmed at the 2nd and 98th percentiles to reduce the influence of extreme values. The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Table 10: Test of continuity of the covariates at the threshold

	Voluntary buffers	Risk-weighted assets (ln)
Point Estimator		
MSE-optimal bandwidth	-0.025	-0.005
	(0.305)	(0.912)
Bandwidth	[260,700]	[273,1678]
Observations	[491,176]	[491,368]
CER-optimal bandwidth	-0.044	-0.088
	(0.342)	(0.558)
Bandwidth	[194,522]	[204,1251]
Observations	[491,176]	[491,368]

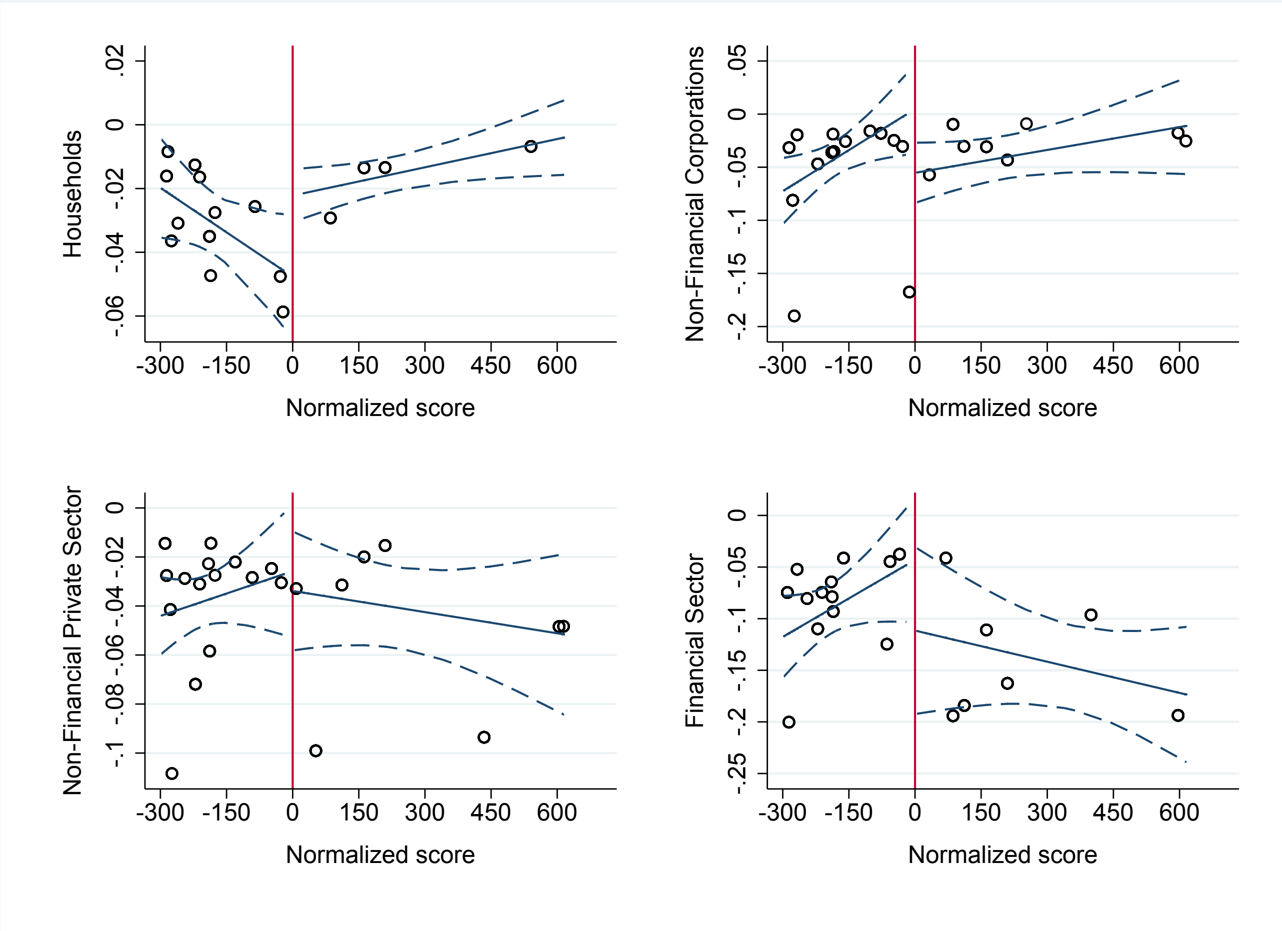
Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII). The dependent variables are the voluntary capital buffer (CET1 excluding requirements) in column (1) and risk-weighted assets (ln) in column (2). Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are performed. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively. Given the bank's inability to manipulate the value of the score received, covariates just above and below the cutoff should be similar across treated and untreated banks. There is no significant evidence of the existence of a discontinuity between the covariates of both treated and untreated groups.

Figure 6: Lending: Average effect of the OSII buffer (cross-border subsidiaries)



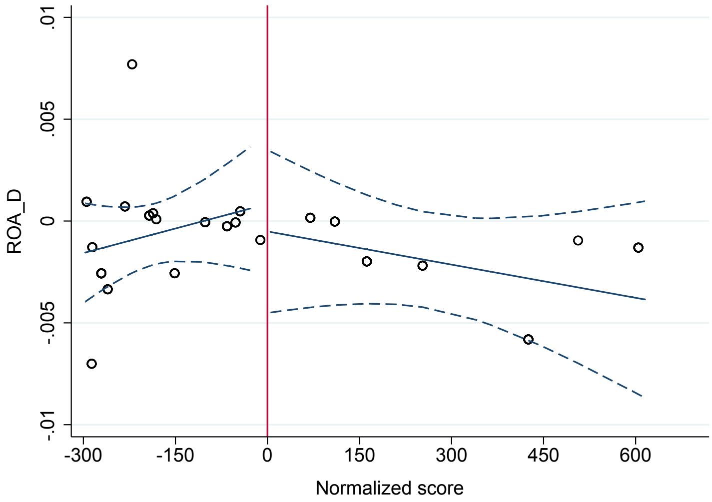
Notes: Regression discontinuity design graph for the quarterly credit growth (difference of log credit) for cross-border subsidiaries. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values. The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 7: Risk-taking: Average effect of the OSII buffer (cross-border subsidiaries)



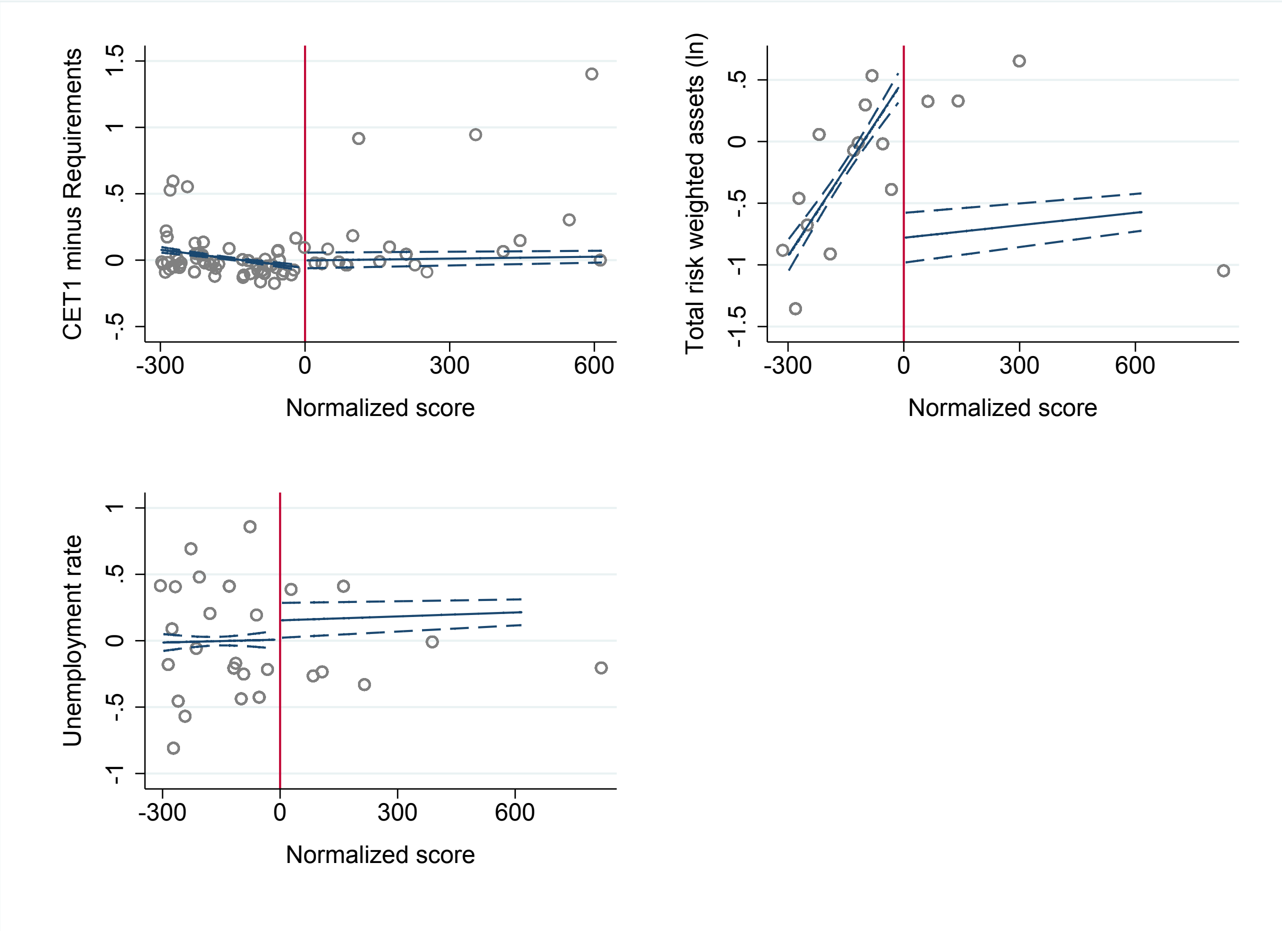
Notes: Regression discontinuity design graph for the quarterly change in the risk-weights for cross-border subsidiaries. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values. The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 8: Profitability: Average effect of the OSII buffer (cross-border subsidiaries)



Notes: Regression discontinuity design graph for the quarterly change in profitability (ROA) for cross-border subsidiaries. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values. The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval.

Figure 9: Test of continuity of the covariates



Notes: Test of continuity for covariates (Skorovron and Titiunik, 2015). The vertical axis displays the outcome variable. The horizontal axis measures the normalized score (i.e. the distance from the threshold). The central line plots fitted values of the regression dependent variable on a first-order polynomial in the score distance from the threshold, estimated separately on each side of the cutoff. The lateral lines represent the 95 percent confidence interval. Given the bank's inability to manipulate the value of the score received, covariates just above and below the cutoff should be similar across treated and untreated banks.

Table 11: Treatment effect for multiple bandwidths

Δ *Log Credit* **Left Bandwidth**					
HH		100	150	200	250
Right Bandwidth	300	0.072	0.042	0.033	0.032
	400	0.070	0.042	0.033	0.032
	500	0.064	0.039	0.031	0.030
	600	0.052	0.033	0.027	0.026
	700	0.047	0.033	0.027	0.025
	800	0.045	0.033	0.027	0.025
	900	0.043	0.033	0.027	0.026

Left Bandwidth					
NFC		100	150	200	250
Right Bandwidth	300	-0.057	-0.036	-0.040	-0.040
	400	-0.054	-0.029	-0.034	-0.033
	500	-0.071	-0.039	-0.042	-0.039
	600	-0.085	-0.050	-0.053	-0.049
	700	-0.101	-0.066	-0.068	-0.064
	800	-0.106	-0.073	-0.074	-0.070
	900	-0.104	-0.074	-0.076	-0.071

Left Bandwidth					
NFPS		100	150	200	250
Right Bandwidth	300	0.070	0.064	0.055	0.053
	400	0.073	0.060	0.051	0.049
	500	0.065	0.052	0.043	0.042
	600	0.056	0.047	0.040	0.039
	700	0.032	0.039	0.033	0.032
	800	0.024	0.035	0.030	0.029
	900	0.020	0.032	0.027	0.027

Left Bandwidth					
FS		100	150	200	250
Right Bandwidth	300	-0.694	-0.290	-0.226	-0.180
	400	-0.667	-0.311	-0.253	-0.205
	500	-0.593	-0.259	-0.213	-0.172
	600	-0.547	-0.228	-0.188	-0.153
	700	-0.519	-0.210	-0.173	-0.142
	800	-0.496	-0.199	-0.162	-0.134
	900	-0.475	-0.189	-0.153	-0.126

Left Bandwidth					
PS		100	150	200	250
Right Bandwidth	300	0.664	0.248	0.198	0.211
	400	0.629	0.253	0.205	0.217
	500	0.589	0.222	0.177	0.192
	600	0.537	0.195	0.155	0.173
	700	0.474	0.168	0.132	0.152
	800	0.431	0.151	0.118	0.139
	900	0.392	0.137	0.107	0.128

Δ *Avg. Risk-weights* **Left Bandwidth**						
HH		100	150	200	250	300
Right Bandwidth	300	-0.040	-0.014	-0.014	-0.012	-0.011
	400	-0.036	-0.014	-0.014	-0.012	-0.011
	500	-0.036	-0.014	-0.013	-0.011	-0.010
	600	-0.034	-0.014	-0.014	-0.011	-0.010
	700	-0.033	-0.015	-0.014	-0.012	-0.010
	800	-0.031	-0.014	-0.013	-0.011	-0.010
	900	-0.027	-0.013	-0.012	-0.010	-0.009

Left Bandwidth						
NFC		100	150	200	250	300
Right Bandwidth	300	-0.072	-0.042	-0.034	-0.027	-0.022
	400	-0.067	-0.039	-0.032	-0.025	-0.020
	500	-0.066	-0.039	-0.032	-0.025	-0.020
	600	-0.068	-0.040	-0.033	-0.026	-0.021
	700	-0.068	-0.040	-0.034	-0.027	-0.022
	800	-0.066	-0.040	-0.034	-0.027	-0.022
	900	-0.063	-0.039	-0.032	-0.026	-0.021

Left Bandwidth						
NFPS		100	150	200	250	300
Right Bandwidth	300	-0.056	-0.036	-0.030	-0.024	-0.019
	400	-0.049	-0.033	-0.028	-0.023	-0.018
	500	-0.049	-0.033	-0.028	-0.023	-0.018
	600	-0.049	-0.032	-0.028	-0.023	-0.018
	700	-0.050	-0.034	-0.030	-0.024	-0.020
	800	-0.049	-0.034	-0.030	-0.025	-0.020
	900	-0.047	-0.033	-0.029	-0.024	-0.019

Left Bandwidth						
FS		100	150	200	250	300
Right Bandwidth	300	-0.004	0.002	-0.002	-0.007	-0.008
	400	-0.005	0.001	-0.003	-0.008	-0.009
	500	-0.011	-0.004	-0.008	-0.013	-0.013
	600	-0.014	-0.007	-0.010	-0.014	-0.015
	700	-0.015	-0.007	-0.010	-0.014	-0.015
	800	-0.014	-0.007	-0.010	-0.014	-0.014
	900	-0.013	-0.006	-0.009	-0.013	-0.013

Δ *Avg. ROA* **Left Bandwidth**						
		100	150	200	250	300
Right Bandwidth	300	0.007	0.000	-0.001	0.000	0.001
	400	0.005	0.000	-0.001	0.000	0.000
	500	0.005	-0.001	-0.001	0.000	0.000
	600	0.004	-0.001	-0.001	-0.001	0.000
	700	0.003	-0.001	-0.002	-0.001	0.000
	800	0.003	-0.001	-0.002	-0.001	0.000
	900	0.003	-0.002	-0.002	-0.001	0.000

Notes: (Robustness check for) Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII). The dependent variables are (1) the quarterly difference in log credit (left hand side panel), (2) the quarterly change in the average risk-weights (first four tables on the right hand side panel) and (3) the quarterly change in the return-on-assets (final table on the right hand side panel). Local linear regressions with a triangular kernel using multiple bandwidths on both sides of the threshold are performed. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2^{nd} and 98^{th} percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level.

Table 12: Risk-taking (STA): Average effect of the OSII buffer (all subsidiaries)

	Households	Non-financial corporations	Non-financial private sector	Financial sector
Δ Avg. Risk-weights				
MSE-optimal bandwidth	-0.002	-0.029***	-0.019	-0.024
	(0.806)	(0.006)	(0.132)	(0.180)
Bandwidth	[272,855]	[280,1086]	[274,803]	[409,2017]
Observations	608	712	568	507
CER-optimal bandwidth	0.002	-0.044**	-0.025	-0.021
	(0.910)	(0.029)	(0.183)	(0.268)
Bandwidth	[204,742]	[209,811]	[205,599]	[308,1520]
Observations	608	712	568	507

Notes: Fuzzy regression discontinuity design estimates for the effect of the ultimate parent identification as systemically important (OSII) on affiliated banks' risk-taking, for portfolios under the standard approach. The dependent variable is the quarterly change in the average risk-weights. Local linear regressions with a triangular kernel using both the MSE-optimal and the CER-optimal bandwidths are used. Covariates include: voluntary capital buffer (CET1 minus requirements), risk-weighted assets (in logs) and the country's unemployment rate. Regressions include quarter fixed effects, country fixed effects, interacted time and country fixed effects and a polynomial of degree one in the score distance from the threshold. The data is trimmed at the 2$^{\text{nd}}$ and 98$^{\text{th}}$ percentiles to reduce the influence of extreme values on the precision of the estimates. Standard errors are clustered at the bank level. ***, **, and * denote significance at the 1, 5 and 10 percent level, respectively.

Table 13: Cerulli and Ventura (2019) parallel trend F (test for joint significance on the leads)

	P-value
F-test on leads	
Short-term debt	0.130
Long-term debt	0.685
Equity	0.409

Notes: This table reports the results for the Cerulli and Ventura (2019) parallel trend F-test for the joint significance on the leads. This test is constructed by estimating the dynamic regression, $Y_{i,t} = \mu_{i,j} + \lambda X_{i,t} + \beta_{t+2} D_{i,t+2} + \beta_{t+1} D_{i,t+1} + \beta_t D_{i,t} + \beta_{t-1} D_{i,t-1} + \beta_{t-2} D_{i,t-2} + \varepsilon_{i,t}$, where $Y_{i,t}$ represents the outcome variable of interest, $\mu_{i,j}$ represents the fixed effects, $D_{i,t}$ represents the binary treatment (at different points in time) and $X_{i,t}$ is a matrix containing the matching covariates, which are the CET1 voluntary buffer, the logged risk-weighted assets and the country's unemployment rate. The coefficients for the leads β_{t+2} and β_{t+1} are jointly tested for significance. Since the test fails to reject the hypothesis of the lead coefficients being statistically different than zero, it is assumed that $Y_{i,t}$ is determined by the contemporaneous and lagged values of the treatment, and hence the necessary condition for the existence of the parallel pre-treatment trends holds.

Figure 10: Rosenbaum and Rubin (1983) test for the balancing property

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****************************************************
Algorithm to estimate the propensity score
****************************************************

The treatment is DUMMY_OSII_TREATMENT

DUMMY_OSII_ |
  TREATMENT |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        104       46.43       46.43
          1 |        120       53.57      100.00
------------+-----------------------------------
      Total |        224      100.00

Estimation of the propensity score

Iteration 0:   log likelihood = -154.69305
Iteration 1:   log likelihood = -145.92322
Iteration 2:   log likelihood = -145.87935
Iteration 3:   log likelihood = -145.87935

Probit regression                               Number of obs     =        224
                                                LR chi2(3)        =      17.63
                                                Prob > chi2       =     0.0005
Log likelihood = -145.87935                     Pseudo R2         =     0.0570

------------------------------------------------------------------------------
DUMMY_OSII~T |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    CET1MREQ |  -9.103876   5.044638    -1.80   0.071    -18.99118    .7834323
UNEMPLOYMENT |  -.0498358   .0171576    -2.90   0.004    -.0834642   -.0162075
OG_RWA_TOT~N |   .2284831   .1311378     1.74   0.081    -.0285422    .4855084
       _cons |  -4.954556    3.66567    -1.35   0.177    -12.13914    2.230025
------------------------------------------------------------------------------
```

(a)

```
Description of the estimated propensity score

                 Estimated propensity score
-------------------------------------------------------------
      Percentiles      Smallest
 1%     .2136518       .2116445
 5%     .2477273        .213201
10%     .3334824       .2136518       Obs                 224
25%     .4521754       .2180915       Sum of Wgt.         224

50%     .5524888                      Mean           .5345985
                        Largest       Std. Dev.      .1398643
75%     .6511961        .752037
90%     .6906945       .7660048       Variance        .019562
95%     .7254106       .7690903       Skewness      -.5401697
99%     .7660048       .7942112       Kurtosis       2.521604

******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************

The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks
```

(b)

```
*************************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
*************************************************************

The balancing property is satisfied

This table shows the inferior bound, the number of treated
and the number of controls for each block

  Inferior |
  of block | DUMMY_OSII_TREATMENT
 of pscore |         0          1 |     Total
-----------+----------------------+----------
        .2 |        18          1 |        19
        .3 |        11         11 |        22
        .4 |        45         54 |        99
        .6 |        30         54 |        84
-----------+----------------------+----------
     Total |       104        120 |       224

*********************************************
End of the algorithm to estimate the pscore
*********************************************
```

(c)

Notes: This output reports the results from Rosenbaum and Rubin (1983) test for the balancing property. The algorithm for this test finds that the optimal number of blocks given the covariates - CET1 voluntary buffer, logged risk-weighted assets and the country's unemployment rate - for which the propensity score (calculated in the probit regression) does not differ for treated and control banks is 5. It then tests the balancing property for each covariate within each interval. As observed, the balancing property is satisfied, which ensures that the covariates are suited to perform the matching between treated and control banks. A detailed explanation of the algorithm is presented in Becker and Ichino (2002).

Acknowledgements

The authors would also like to express their since gratitude to Linda Goldberg, Martin Brown, Christoph Basten, Alessandro Scopelliti and Matic Petricek for their insightful discussions. The authors would also like to thank all the conference participants at the Norges Bank and IBEFA workshop on “Prepared for the next crisis? The costs and benefits of financial regulation”, the 4th BIS-CGFS workshop on “Research on global financial stability: the use of BIS international banking and financial statistics”, the 7th workshop of the Monetary Policy Committee Task Force on Banking Analysis for Monetary Policy and the 4rd workshop of ESCB Research Cluster on Financial Stability, Macroprudential Regulation and Microprudential Supervision for their excellent comments. 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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PDF ISBN 978-92-899-4414-4 ISSN 1725-2806 doi:10.2866/55430 QB-AR-20-149-EN-N