# The Capital Buffer Calibration for Other Systemically Important Institutions – Is there too much Country Heterogeneity?

December 6, 2018

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**Abstract**

Identifying systemically important financial institutions is a key topic in financial regulation. The European Banking Authority (EBA) has devised a buffer guideline for identifying other systemically important institutions (OSIIs) to address this issue. This guideline defines how to identify "OSIIs" by a scoring process, but crucially does not go as far as specifying an assignment process of scores into buffers. In this study, we model this assignment process as a Nash bargaining problem between the regulator and the banks' representative. Based on a sample of 186 European banks, we derive and estimate the variables that influence the bargaining solution. We also quantify the extent of the heterogeneity in the buffer attribution between countries, which accounts to around 83 bn EUR in additional capital requirements.

*Keywords:* systemic risk; financial stability; macroprudential policy; other systemically important institutions

## 1. Introduction: Systemic risk and financial regulation

The recent financial crisis has shown that identifying systemically important financial institutions is a key topic in financial regulation. The depth and severity of the financial crisis were clearly amplified by the assumption that certain financial institutions were too big to fail. At least many market participants made sometimes incorrect assumptions about an institution being too big to fail. The Lehman Brothers serve as such an example, as it was not saved, the shock waves through the financial system were measurable through stock market and CDS data from other financial institutions (Dumontaux and Pop, 2013). It highlights the risk to financial systems that idiosyncratic shocks can easily spread through the entire system. In the context of interconnected financial institutions Iori et al. (2006) refers to this risk

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as "systemic risk". Clearly, the Lehman Brothers was very interconnected to other financial institutions. To make matters worse markets and policy makers most probably did not correctly anticipate the system risk or its consequences arising from the Lehman Brothers' default.

Especially since the financial crisis 2007–2008, most policy makers agree that safeguarding financial stability is a key driver for financial regulation and most definitely systemic risk poses a significant risk to financial stability. In ECB (2009), financial stability is defined as *"a condition in which the financial system - comprising of financial intermediaries, markets and market infrastructures - is capable of withstanding shocks and the unraveling of financial imbalances, thereby mitigating the likelihood of disruptions in the financial intermediation process which are severe enough to significantly impair the allocation of savings to profitable investment opportunities."*

Without going into too many details, there are two relatively new approaches to quantify systemic risk. First, the academic approach to quantifying systemic risk is shaped by contributions of Acharya et al. (2010), which is developed into SRisk (Brownlees and Engle, 2016; Engle et al., 2014), and of Adrian and Brunnermeier (2016), who introduce the ΔCoVaR concept. In a nutshell, SRisk quantifies the capital shortfall of a bank given a strong market decline and ΔCoVaR estimates the value-at-risk of the system as a whole when a particular bank faces distress, i.e. experiences a tail event.

Second, in the regulatory approach, simpler concepts are applied to identify systemically important institutions:[2] Under current Basel III rules, the buffer for systemically important institutions, as well as their current implementations (FED, 2015; EBA, 2014) aims to address the risk stemming from the failure of an institution. In EBA (2014) there is a scoreboard approach where a number of indicators weighted by the size of the banking system are linearly combined to an overall score. A higher score should reflect a greater risk to the financial system if the institution fails. However, most critically there is no guideline in EBA (2014) how to translate the score into a buffer. In line with the literature, (Wheelock and Wilson, 2000; Rime, 2001), EBA (2014) claims that the OSII buffer should reduce an institution's probability of default and therefore reduces the expected losses caused by this institution's failure in the financial system.

The reasons for the two different approaches are quite simple: Most importantly, the applications of SRisk and ΔCoVaR require the bank to be publicly listed. However, according to Siebenbrunner et al. (2017), this is only true for 22% of banks in the US, 4% in the UK, 3% in France and as little as 1% in Germany. From a regulatory point of view, SRisk and ΔCoVaR are not applicable to identify all OSIIs in the European union. On the other hand, the OSII score can be calculated for every bank and if the score is above a certain threshold, then this bank is classified as an OSII (see Section 3 for more details).

Siebenbrunner et al. (2017) combine the academic and the regulatory approach to systemic risk by setting up four different interbank contagion channel models based on extensions of the network clearing algorithm by Eisenberg and Noe (2001). Based on complete interbank network data, which are highly sensitive and unfortunately not available in all European countries, these contagion channels include

[2] We refer to both the buffers for globally and other systemically important institutions (BIS, 2012, 2013)

first-round, $n^{th}$, asset-fire sales and mark-to-market contagion losses. Further, Siebenbrunner et al. (2017) and Siebenbrunner and Sigmund (2018a) empirically show that the indicators in the EBA (2014) OSII scoring method are good predictors for these contagion losses. Thus, in the absence of interbank network data, the variables in the OSII score approach are still useful for predicting contagion losses. Moreover, Siebenbrunner and Sigmund (2018b) find empirical evidence that contagion losses are not priced in the interbank loan and deposit rates, which leads to welfare losses as theoretically shown by Acemoglu et al. (2015). As consequence, the OSII buffer might be a necessary macroprudential instrument to correct for this market failure.

Our contribution to the literature is threefold. To the best of our knowledge, we are the first paper that analyzes how the European union member states fill the missing link between the OSII score and the OSII buffer for all 186 European OSIIs. Second, we are the first to show that the OSII buffer assignment is very heterogeneous in Europe, although there is a unified EBA (2014) guideline how to identify and score OSIIs. In the process, we estimate an ordered probit model and a Poisson count data model to identify a high degree of country heterogeneity in the OSII buffer assignment. Third, we purpose a theoretical model that explains how the OSII buffer assignment process could work. We describe the OSII buffer assignment process as an (at least) implicit Nash bargaining problem (Nash, 1953) between the regulator and banks' representatives. Assigning the OSII buffer can be seen as a variant of "the diving a dollar" game (Nash, 1953), where the regulator prefers to assign an optimal OSII buffer, depending on certain bank characteristics and the banks' representatives prefers a buffer of 0%. In contrast to the usual theoretical approach, that calculates the Nash bargaining solution based on ex-ante defined parameters (such as the bargaining power of the players), we estimate these "bargaining parameters" based on the OSII buffer assignment decisions of all 186 OSIIs in Europe.

The remainder of the paper is structured as follows: Section 2 describes the data used. Section 3 gives a formal definition of the EBA scoring process (EBA, 2014). In Section 3, we describe the OSII buffer assignment problem as a Nash bargaining solution. In Section 5, we describe the empirical models to analyze the OSII buffer assignment process. In Section 6, we describe our results starting with the ordered probit model to highlight the country heterogeneity in the OSII buffer assignment. Next, we quantify the heterogeneity in a capital requirement scheme simulation. We also discuss the estimated parameters of the Nash bargaining solution. Section 7 concludes and provides important policy recommendations.

## 2. Data

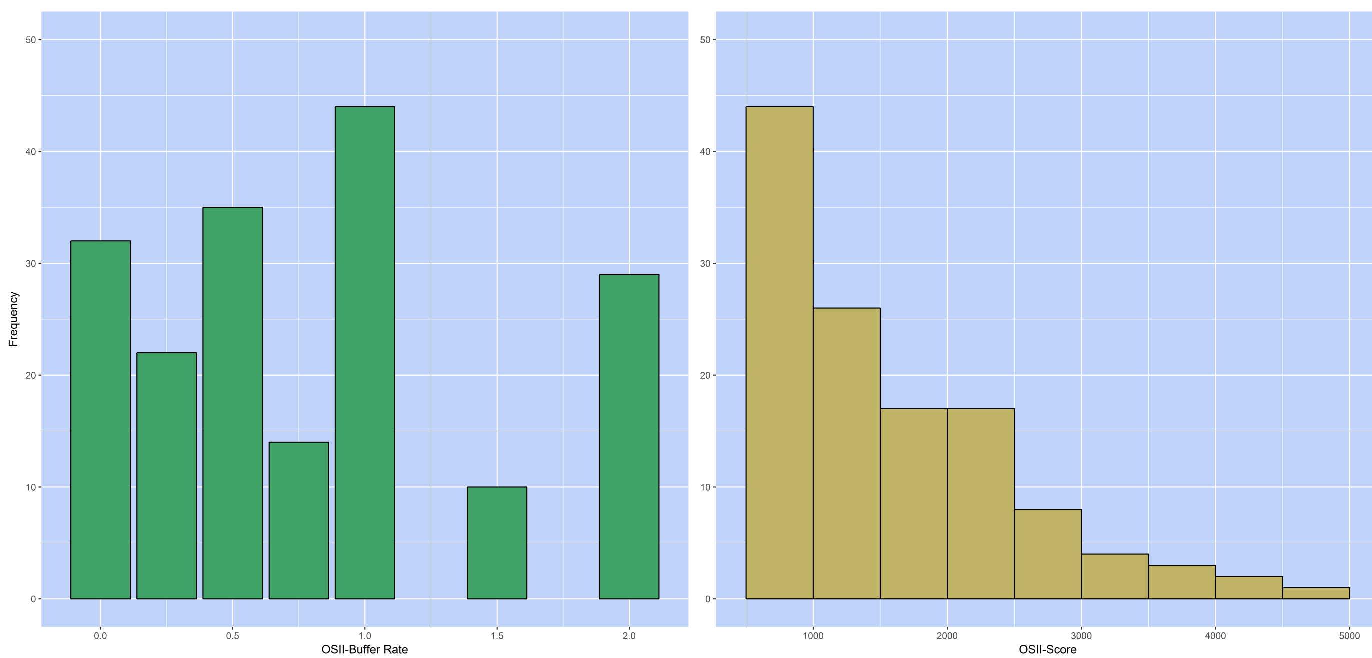
Our dataset consists of three different sources. First, we describe the OSII score and buffer data available from the European systemic risk board. Second, we add bank-specific variables from SNL Financial Institutions and Bank data. Third, we add worldwide governance indicators from Kaufmann et al. (2011).

### 2.1. *OSII-Data*

All data on OSII buffers and OSII scores are based on the publications of the European union member state authorities to the European Systemic Risk Board (ESRB).[3] The regulatory basis for this publication is the European Banking Authority (EBA, 2014) and is defined in the Article 131(3) of Directive 2013/36/EU (CRD). According to this document, the European union member state authorities should calculate an OSII buffer rate for each bank according to the EBA scoreboard approach (see Table 1).

In our analysis, we include banks from European union member states and Iceland that report the OSII buffers of their banks to the ESRB database. This leads to 283 observations, with 186 banks from 2015 to 2017 in 28 countries. For the estimations we use all 283 observations but we do not include bank fixed effects because of the irregular publication of the OSIIs.[4] In Figure 1, we make the first important observation: The difference in the distributions of the OSII buffers and the OSII scores already implies that the OSII scores are not soley responsible for the resulting OSII buffer sizes.

Figure 1: OSII Buffers vs. OSII Score Frequency




Source: ESRB database.
https://www.esrb.europa.eu/national_policy/systemically/html/index.en.html
The left histogram shows the frequency of OSII buffers between 0% and 2%. The right histogram shows the frequency of OSII scores between 0 and 5000.

[3]All OSII buffers for European union member state banks are available on https://www.esrb.europa.eu/national_policy/systemically/html/index.en.html.

[4]We also estimate all models with only 186 observations and find very similar results. Some of these robustness checks can be found in Appendix B.

### 2.2. *Other Explanatory Variables*

In addition to the bank specific variables captured in the OSII scoring process (see Section 3), we include the Tier 1 capital ratio, the operating income ratio (income divided by total assets) and the non-performing loan ratio as possible predictors for the OSII buffer. Our final set of predictors is based on Kaufmann et al. (2011) and includes the rule of law and regulatory quality. According to Kaufmann et al. (2011) rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Whereas regulatory quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

## 3. The EBA OSII Scoring Process

In Article 131(3) of Directive 2013/36/EU (CRD) the following guideline defines the scoring process for assessing the systemic importance of institutions.

Table 1: Scoring Process

| Criterion | Indicators | Weight |
|---|---|---|
| Size | Total assets | 25% |
| Importance | Value of domestic payment transaction | 8.33% |
| | Private sector deposits from depositors in the EU | 8.33% |
| | Private sector loans to recipients in the EU | 8.33% |
| Complexity/Cross-border activity | Value of OTC derivatives (notional) | 8.33% |
| | Cross-jurisdictional liabilities | 8.33% |
| | Cross-juridictional claims | 8.33% |
| Interconnectedness | Intra financial system liabilities | 8.33% |
| | Intra financial system assets | 8.33% |
| | Debt securities outstanding | 8.33% |

Source: EBA (2014).

The weighted numbers of the scoring process in Table 1 are then used to calculate the OSII score of bank $i$ as follows:

$$\text{OSII-Score}_i = 10,000 * \sum_{Ind. \in \text{OSII-Indicators}} w^{Ind.} \frac{Ind._i}{\sum_{j=1}^{N} Ind._j} \tag{1}$$

Where $N$ is the number of banks in a specific country and *Size*, *Importance*, *Complexity* and *Interconnectedness* are the weighted criteria of Table 1. By dividing each weighted criteria by the weighted sum (across all banks in a country) of each criteria, it is possible to compare OSII scores across countries. In this step, the EBA scoring process adjusts for different sizes of the banking sector across countries. Multiplying the result by 10,000 makes sure that each bank has a score in the open interval $(0, 10, 000]$.[5] The OSII score more or less reflects a weighted "market share" of bank $i$ in country $j$.

This score is re-calculated annually by the designated authorities and must be publicly accessible. The scores are used in a two step procedure to determine OSIIs:

(1) If a specific bank has more than 350 basis points, authorities have to declare this institution as an OSII. The authorities are allowed to increase or decrease the threshold of 350 in a range between 275 and 425 basis points to take into account member states specific characteristics of the banking sector.

(2) If there are further institutions which are relevant, authorities can designate them as OSIIs. However, institutions with a score of 4.5 basis points or lower shall not be designated as OSIIs.

In addition to the assignment of OSIIs, the authorities of each country should, with accordance to the EBA score, establish an appropriate OSII buffer. For institutions with a higher systemic importance, higher buffer rates should be calibrated. This additional buffer can be established by the authorities up to 2% of the total risk exposure amount consisting of Common Equity Tier 1 capital. Due to this additional capital the stability of individual OSII should be strengthened and should prevent a "domino-effect" in national banking systems in a bust phase. A common scheme for defining an O-SII buffer with an underlying score does not exist. Country's authorities have the possibility to set their buffer rate according to their own method. Analyzing this decentralized decision making about the translation from score to buffer rate is the main focus of our empirical work.

Some facts about the scoring process in combination with the Systemic Risk Buffer (SyRB) has to be mentioned. There are three important exception defined in Article 131 of Directive 2013/36/EU (CRD) we take into account in our study:

(1) §8 if an OSII is a subsidiary of either a GSII or an OSII with a parent institution in an other European country the OSII buffer shall not exceed the buffer on the consolidated level.
(2) In §14 of this article it states that if an institution, *"on an individual or sub-consolidated basis is subjected to an OSII buffer and a systemic risk buffer (...) the higher of the two shall apply"*.
(3) In §15 if the SyRB is applied on all exposures in the member state but is not applied on exposures outside the member state, the OSII buffer and the SyRB shall be cumulative.

The §8 of this directive is not a statistical problem, since this incident seldom happens. The §§14 and 15 are more statistically relevant. The limit of the SyRB buffer is 3% and the limit of the OSII buffer is 2%. If a country takes the higher of the two, it could happen that there is only a SyRB, but not an OSII-buffer. This could suggest that certain countries (CZ and DK) do not set an OSII-buffer at all. Removing these two countries from our data does not change our results. We present the results in Appendix Appendix

[5] Hypothetically, a score of 10,000 would imply that there was only one bank in a specific country. A score of close to 0 would imply that a bank has a balance sheet sum close to 0.

C. The cumulative part could also lead to a similar problem. As a consequence, we control for these possibilities by adding two dummy variables, $HigherSyRB$ and $SumSyRB$, to some models.

#### 4. The OSII Buffer Assignment Process

As already mentioned, there is no guidance for the OSII buffer assignment process. We assume that the OSII buffer assignment process is a bargaining process between the regulatory authority and banks' representatives. In some countries, it might be possible that only one of these parties is solely responsible for the OSII buffer decision. However, empirical evidence suggests that the OSII buffer assignment is also a political process. As a consequence, we first analyze how the OSII buffer assignment process should be implemented within the national macroprudential institutional framework. Although it has not been implemented by all countries in our sample, there is an ESRB recommendation on the macroprudential institutional framework (ESRB, 2011b). Most importantly, ESRB (2011b) states that *"macro-prudential policy can be pursued by either a single institution or a board composed of several institutions, depending on the national institutional frameworks [..]"* and that *"the national central banks should have a leading role in macro-prudential oversight because of their expertise and their existing responsibilities in the area of financial stability."* As a consequence, in each country a macroprudential authority should be responsible for setting an OSII buffer. In a second step, the same or another authority, namely the designated authority is then responsible for issuing an administrative decision on the OSII buffer to the respective banks.

Within the national macroprudential institutional framework, there are several possibilities. In some countries the macroprudential authority and the designated authority are the same (BE, CZ, EE, IE, GR, FR, CY, LT, HU, MT, PT, RO, SK, FI, SE and UK). In other countries, these authorities are separated (BG, DK, DE, ES, HR, IT, LV, LU, NL, AT, PL and SI). In two countries, ES and IT no macroprudential authority has been established yet. Within these two general macroprudential institutional frameworks, there are also notable differences. In BE, CZ, EE, IE, GR, CY, LT, HU, MT, PT and SK the central bank in the responsible macroprudential and designated authority. In FR, RO, FI, SE and UK the financial market authority has both responsibilities. In those countries where the responsibilities are separated, different institutions are involved.[6] In some countries such as Austria and Germany the macroprudential authority is designed as a (financial stability) committee where more than two institutions have at least one member with voting power.[7]

After describing the different national macroprudential institutional frameworks, we set up a Nash bargaining problem (Nash, 1953) with two players, the regulator and banking representatives. More formally, we arrive at the following definition:

[6] See https://www.esrb.europa.eu/national_policy/shared/pdf/esrb.170825_list_national_macroprudential_authorities_national_designated_authorities_in_EUMemberStates.en.pdf for a table with all the details.

[7] In Austria, the financial market authority and the Central Bank send one member each. The Government Debt Committee and the Ministry of Finance send two members.

**Definition 4.1.** *(OSII buffer assignment bargaining problem): The OSII buffer assignment bargaining problem is a pair $(S, d)$, where $S \subset R^2$ is compact and convex, $d \in S$, and there exists $s \in S$ such that $s_i > d_i$ for $i = 1, 2$. The set of all bargaining problems is denoted $B$. A bargaining solution is a function $f^\alpha : B \rightarrow R^2$ that assigns to each bargaining problem $(S, d) \in B$ a unique element of S.*

In Nash (1953), the bargaining problem is not strategically formulated (the complicated details of a bargaining process are left out), but based on axioms (invariance to equivalent utility representations, symmetry, independence of irrelevant alternatives and Pareto efficiency). IN our model, we drop the symmetry axiom, as we later define player specific bargaining weights.

We assume that OSII buffer assignment bargaining problem is solved for every OSII. Thus, it is straightforward to define the set $S$.

$$\begin{aligned} A &= \{(a_1, a_2) \in R^2 : a_1 + a_2 = 2 \text{ and } a_1 \in [0,2], a_2 \in [0,2]\} \\ S &= \{(s_1, s_2) \in R^2 : (s_1, s_2) = (u_1(a_1), u_2(a_2)) \text{ for some } (a_1, a_2) \in A\} \end{aligned} \tag{2}$$

We assume that player 1 is the regulator and wants to set a buffer between 0 and 2, depending on certain parameters. Player 2 is a bank representative and has to "pay" for the OSII buffer by holding more capital. Very importantly, $d = (d_1, d_2)$ from Definition 4.1 is called the threat point, which would be the outcome if the players do not reach an agreement. It is not ex-ante clear what these threat points would be but clearly $(d_1, d_2) \in A$. For each OSII there is a buffer. Further restrictions on the threat points could be minimal standard set by an ESRB or EBA recommendation/guideline. In any case, a threat point of $d_2 = 0$ might not be optimal from a macroprudential point of view, especially for banks with a high OSII score.

We also assume that $u_1(a_1)$ (the utility function of the regulator) is a differentiable function for each bank.[8] In particular, based on the OSII score and probably the regulator's buffer assignment model, the regulator calculates an optimal OSII buffer. From Eq. (2), we see that $a_2 = 2 - a_1$, thus $u_2(2 - a_1)$.

We finally state the Nash bargaining solution without the symmetry assumption:

**Definition 4.2.** *(OSII buffer bargaining solution):*

$$\mathbb{N} = \underset{(d_1,d_2)\leq(u_1(a_1),u_2(1-a_1))\in S}{\operatorname{argmax}} (u_1(a_1) - d_1)^\alpha (u_2(1 - a_1) - d_2)^{1-\alpha} \tag{3}$$

$\mathbb{N}$ is the Nash product for the bargaining process between the regulator and the banks' representatives. Depending on $\alpha$ given the assumptions of Definition 4.1, there is a unique solution to the problem:

[8] Differentiability is not a necessary assumption to find a solution but simplifies the derivation considerably.

$$\begin{aligned}\frac{\partial \mathbb{N}}{\partial a_1} &= \alpha\,(u_1(a_1)-d_1))^{\alpha-1}\,\frac{\partial u_1(a_1)}{\partial a_1}\,(u_2(2-a_1)-d_2)^{1-\alpha}+\\ &\quad (u_1(a_1)-d_1)^{\alpha}\,(1-\alpha)\,(u_2(2-a_1)-d_2)^{-\alpha}\,\frac{\partial u_2(2-a_1)}{\partial a_1}=0\\ &= \alpha\frac{\partial u_1(a_1)}{\partial a_1}\,(u_2(2-a_1)-d_2)+(u_1(a_1)-d_1)\,(1-\alpha)\frac{\partial u_2(2-a_1)}{\partial a_1}=0\end{aligned} \tag{4}$$

If we set $d_1 = d_2 = 0$, $\alpha = 1/2$ and make $u_1, u_2$ linear in $a_1$, then we arrive at the well-known "divide a penny" Nash bargaining solution of $a_1^* = 1$. However, the OSII buffer assignment is not such a simple division of a penny.

Aside from these theoretical considerations (which are numerous in the literature), there are surprisingly one a few papers that ask the most important question: What variables influence $d_1, d_2, s_1, s_2$, $\alpha$ and hence the bargaining outcome $OSIIB^*$? One notable exception is the Nobel Prize winning Diamond–Mortensen–Pissarides theory of equilibrium unemployment (Pissarides, 2000). In this theory, it is assumed that wage is divided by a Nash bargaining between the employee and the employer in a matched vacancy–job searcher pair.

Thus, we start by defining the utility function of the regulator. We make the following assumptions: (1) $u_1(a_1)$ is linear. (2) There is an optimal OSII buffer ($OSIIB^*$) from the regulator's point of view, which positively depends on the OSII score.

Next, we make assumption about the threat point $d_1$. Under the current regulation, where in most countries the higher of the SyRB and OSII buffer is binding, we consider the SyRB as a potential threat point.

The bargaining weight of the regulator is most probably determined by the national macroprudential institutional framework. We proxy this by a country dummy and by the variable regulatory quality (see Section 2.2).

The utility function of the banks' representatives is also assumed to be linear in $a_1$ over the interval $[0, 2]$. A lower OSII buffer is assumed to increase the utility, even if a potential buffer is not binding, banks' representatives still prefer a higher "management buffer" (difference between the current capital ratio and the regulatory minimum). is also part of the utility function. It is easier to accept an OSII buffer, if it is not binding. The threat point $d_2$ of the banks' representatives also depends on the SyRB. We assume that the tier 1 capital ratio and the operating income ratio are parts of the banks' representative threat point $d_2$.

With these assumptions, we further simplify Eq. (4)

$$\begin{aligned}0 &= \alpha(2-OSIIB^*-(\beta_1 T1CR+\beta_2 SyRB+\beta_3 OIR))-(1-\alpha)(OSIIB^*-(\gamma_1 OSIIS+\gamma_2 SyRB))\\ OSIIB^* &= 2\alpha+\gamma_2(1-\alpha)*OSIIS-\alpha*\beta_1 T1CR-\alpha*\beta_3 OIR+[(1-\alpha)\gamma_1-\alpha\beta_2]SyRB\end{aligned} \tag{5}$$

From the theoretical solution in Eq.(5), we see that the bargaining power of the regulator partially defines the coefficient of all variables. As a consequence, we would need to estimate an OSII buffer bargaining model for each country based on a very limited number of observations to exactly derive the structural parameters $\alpha, \beta_1, \beta_2, \gamma_1$ and $\gamma_2$ We, therefore, introduce a country dummy and the variable regulatory quality in the set of explanatory variables that should capture parts of the "bargaining power" of the regulator and the banks' representatives. Moreover, we only estimate the average structural parameters of OSIIS, T1CR and SyRB across all countries.

$$OSIIB_i^* = \delta_0 + X\delta + \epsilon_i \tag{6}$$

## 5. Empirical Approach

In this section, we describe three different econometric models to explain the buffer for OSIIs. Although the buffer buffers could lie anywhere in the interval $[0, 2]$, they only take values between 0% and 2% in steps of 0.25%. Thus, each regulator seems to choose from a set of eighth possibilities which calls for an ordered probit model. However, given the fact that the eighth different buffer possibilities also have a cardinal interpretation (e.g. 1% is higher not only different from 0.5%), we also apply a second generalized linear model to the data. The count data model with the Poisson distribution is based on the binary choice model. On the down side, in standard count data models there is no upper limit of the dependent variable.

In summary, there is a trade-off between ordered response and count data models: On the one hand the OSII buffer has an upper limit (2% OSII buffer limit), which calls for a ordered response model. On the other hand the cardinal interpretation of OSII buffer, calls for a count data model. As a consequence, we estimate both models and further compare them to an ordinary least squares estimation. All in all the different estimations lead to similar results, strengthening the robustness of our results.

### *5.1. Ordered Probit Model*

From our point of view, the characteristics of the OSII buffer can be best explained by an ordered probit model. As described in Section 2, the OSII buffers take values between 0% and 2% in steps of 0.25%. In the context of an order probit model this could be restated as follows: We choose a set of alternatives k from 0 to 8 with OSII buffers from 0% to 2% in 0.25% steps.

In order to estimate the order probit model, we define a single latent variable $y_i^*$ (which we only observe when it crosses the thresholds, e.g. 0.25% or 0.5%, ect.):

$$\begin{aligned} y_i^* &= x_i'\beta + \epsilon_i \\ y_i &= k \quad \text{if} \quad \alpha_{i-1} < y_i^\star \leq \alpha_j \end{aligned} \tag{7}$$

We observe $y_i = k$ as long as $y_i^\star$ lies in the respective interval. The probability that observation $i$ will select alternatives $1, ..., k, ..., K$ is given by:

$$\begin{aligned}
P(y_i = 0) &= P(\alpha_0 < y_k^\star \leq \alpha_1) \\
P(y_i = 1) &= P(\alpha_1 < y_k^\star \leq \alpha_2) \\
... & \\
P(y_i = k) &= P(\alpha_{k-1} < y_k^\star \leq \alpha_k) \\
... & \\
P(y_i = K) &= P(\alpha_K < y_k^\star \leq \alpha_{K+1})
\end{aligned} \tag{8}$$

Inserting $y_i^*$ from Eq. (7) into Eq. (8) and assuming that $\epsilon_i$ follows a normal distribution, we end up with:

$$\begin{aligned}
P(y_i = k) &= P(\alpha_{k-1} \leq x_i'\beta + \epsilon_i \leq \alpha_k) \\
&= P(\alpha_{k-1} - x_i'\beta \leq \epsilon_i \leq \alpha_k - x_i'\beta) \\
&= P(\epsilon_i \leq \alpha_k - x_i'\beta) - P(\epsilon_i \leq \alpha_k x_i'\beta) \\
&= F(\alpha_k - x_i'\beta) - F(\alpha_{k-1} - x_i'\beta)
\end{aligned} \tag{9}$$

The important parameters $\beta$ and $\alpha_1, ..., \alpha_K$ can be incorporated in the following likelihood function:

$$L(\beta, \alpha) = \prod_{i=1}^{N} \prod_{k=0}^{K} P(y_i = k)^{I(y_i = k)} \tag{10}$$

$I(y_i = k)$ is the indicator function being 1 if $y_i = k$. The log-likelihood function of Eq.(10) follows with:

$$\mathcal{L}(\alpha_k, \beta) = \sum_{i=1}^{N} \sum_{k=1}^{K} \mathbf{I}_{\{y_i = k\}} \log\left(P(y_i = k)\right) \tag{11}$$

Following the usual properties of maximum likelihood estimators, the parameter estimates obtained from maximizing the log-likelihood are consistent and asymptotically normally distributed. The asymptotic variance of the estimated parameters can also be estimated straightforwardly (Wooldridge, 2002).

To measure the goodness of fit, we use the McFadden $R^2$ which is calculated as follow:

$$R^2 = 1 - \frac{\mathcal{L}_{fit}}{\mathcal{L}_0} \tag{12}$$

For estimating the ordered probit model, we use the code of Venables and Ripley (2002). [9]

*5.2. Count Data Model*

In this section, we show how the OSII buffer attribution can be analyzed by a count data model. This model is also based on the binary choice model. It therefore serves as a first robustness check for the ordered probit model.

For the estimation of the count data model, we use the Poisson distribution. Following Cameron and Trivedi (2005) this distribution is described by:

$$P\{Y = y|x\} = \frac{\exp(-\mu)\mu^y}{y!}, y = 0, 1, 2, 3, ... \tag{13}$$

In order to account for the Possion distribution, we transfer the OSII buffers into natural numbers (e.g. $0 \rightarrow 0$, $0.25 \rightarrow 1$, $0.5 \rightarrow 2$ and so on).

The Poisson estimation requires equidispersion which denotes that:

$$E\{y_i|x_i\} = \exp(x_i'\beta) = \mu_i = VAR\{y_i|x_i\} \tag{14}$$

In order to test the validity of our results, we test for equidispersion in Section 6.2 and Section Appendix A.

The Poisson model is estimated via MLE. The Log-likelihood function of the Poisson distribution is given by:

$$\mathcal{L}(\beta) \quad = \quad \textstyle\sum_{i=1}^{N}[-\lambda_i + y_i \log \lambda_i - \log y_i!] \tag{15}$$

The parameter estimations are based on the first order condition of Eq. (15):

$$\sum_{i=1}^{N} (y_i - \exp(x_i'\beta))\, x_i = 0 \tag{16}$$

[9] We also apply the codes of Harrell (2018) and Carroll (2017) which lead to the same results.

As the log-likelihood function is globally concave, the estimation converges rapidly.

To evaluate the goodness of fit of the Poisson estimation, we use the McFadden $R^2$ which is described by:

$$R^2 = 1 - \frac{\mathcal{L}_1}{\mathcal{L}_0} \tag{17}$$

## 6. Empirical results

In the following section, we show our empirical results. In Section 6.1 we present the estimation output of the ordered probit model. We also give an interpretation of the results in terms of conditional probabilities. We estimate how likely it is that a bank $i$ in country $j$ receives an OSII buffer of 1.5%, 1%, 0.5% or 0.25% if its OSII score is 1500.

In Section 6.2 we present a simulation exercise based on the count data model estimation (see Section 5.2) in which we calculate the OSII buffer of bank $i$ if the bank was in Germany (with the German country dummy coefficient). All else equal and assuming that the new OSII buffers would be binding, the additional capital requirements of all banks in the sample would amount to 83.2 billion euros. In the second part of section 6.2 we show the banks with the largest potential capital requirement and surplus based on this simulation. In Section 6.3, we take a deeper look in the OSII buffer assignment process by applying estimation the Nash bargaining solution (see Section 4).

### *6.1. Ordered Probit Model*

In the following section, we show the estimation results for the ordered probit model. The dependent variable, as described in Section 5.1, is the OSII buffer for each bank in each country set by the corresponding regulatory authorities. The independent variables are included in several steps. First, we include the variables *score*, *higher SyRB* and *Cum SyRB*. In the second step, we show the model only with *Score* as an explanatory variable. In the third step, we add 28 country dummy variables.

The interpretation of an ordered probit model is not that easy as in standard estimations (e.g. OLS). Binary and multiple response models focus on estimating probabilities. As a consequence the coefficients in these models can not be directly interpreted, only the sign of the coefficients leads to further interpretation.

In Table 2, we estimate six intercepts, which denotes the K events defined in Eq. (7) and describes what happens in this certain thresholds. As there are no observations with 1.25 and 1.75 the corresponding intercepts are not estimated.

# Table 2: Ordered Probit Model

| | CumHigh Oprobit | Ordered Probit | Ordered Probit with dummy |
|---|---|---|---|
| Score | 0.001 | 0.001 | 0.002 |
| | (0.000) | (0.000) | (0.000) |
| Higher SyRB | 0.192 | | |
| | (0.091) | | |
| Cum SyRB | 0.006 | | |
| | (0.073) | | |
| 0—0.25 | $-0.316^{***}$ | $-0.349^{***}$ | $-4.073^{***}$ |
| | (0.115) | (0.111) | (0.182) |
| 0.25—0.5 | 0.057 | 0.034 | $-2.656^{***}$ |
| | (0.109) | (0.106) | (0.157) |
| 0.5—0.75 | 0.538 | 0.521 | $-1.474^{***}$ |
| | (0.111) | (0.108) | (0.158) |
| 0.75—1 | 0.814 | 0.798 | $-0.931^{***}$ |
| | (0.115) | (0.112) | (0.169) |
| 1—1.5 | 1.843 | 1.813 | 1.094 |
| | (0.148) | (0.145) | (0.237) |
| 1.5—2 | 2.303 | 2.245 | 2.070 |
| | (0.169) | (0.163) | (0.268) |
| BE | | | $-1.779^{***}$ |
| | | | (0.226) |
| BG | | | $-2.358^{***}$ |
| | | | (0.337) |
| CY | | | $-2.508^{***}$ |
| | | | (0.173) |
| CZ | | | $-16.290^{***}$ |
| | | | (0.000) |
| DE | | | $-1.325^{***}$ |
| | | | (0.236) |
| DK | | | $-24.187^{***}$ |
| | | | (0.000) |
| EE | | | $-0.474^{***}$ |
| | | | (0.017) |
| ES | | | $-4.707^{***}$ |
| | | | (0.316) |
| FI | | | $-2.213^{***}$ |
| | | | (0.045) |
| FR | | | $-2.965^{***}$ |
| | | | (0.320) |
| GR | | | $-4.018^{***}$ |
| | | | (0.241) |
| HR | | | $-0.851^{***}$ |
| | | | (0.356) |
| HU | | | $-2.391^{***}$ |
| | | | (0.376) |
| IE | | | $-3.010^{***}$ |
| | | | (0.290) |
| IS | | | 2.475 |
| | | | (0.000) |
| IT | | | $-4.877^{***}$ |
| | | | (0.359) |
| LT | | | $-1.253^{***}$ |
| | | | (0.024) |
| LU | | | $-2.567^{***}$ |
| | | | (0.061) |
| MT | | | $-1.114^{***}$ |
| | | | (0.030) |
| NL | | | $-0.099^{***}$ |
| | | | (0.031) |
| PL | | | $-3.999^{***}$ |
| | | | (0.303) |
| PT | | | $-3.951^{***}$ |
| | | | (0.414) |
| RO | | | $-1.272^{***}$ |
| | | | (0.286) |
| SE | | | 4.727 |
| | | | (0.000) |
| SI | | | $-4.688^{***}$ |
| | | | (0.347) |
| SK | | | $-2.716^{***}$ |
| | | | (0.066) |
| UK | | | $-5.966^{***}$ |
| | | | (0.291) |
| McFadden R2 | 0.100 | 0.096 | 0.493 |
| Num. obs. | 274 | 274 | 274 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
This table shows the results of estimating Eq. (11). In all columns the dependent variable is the OSII buffer.
The table shows the estimated coefficients, t-statistics, McFadden $R^2$ and the number of observations.
CumHigh Oprobit Column: The independent variables is the EBA-score and the two dummy variables Higher SyRB and Cum SyRB.
Ordered Probit Column: The independent variable is the EBA-score (Score). The Threshold variables are the intercepts for each ordinal
Ordered Probit with Country Dummies: In addition to the EBA-Score, we also include a dummy for each country in the sample. The reference country is Austria.
The goodness of fit is calculated via the McFadden $R^2$ described in Eq. (12). The different intercepts denotes the intercept for each OSII buffer. The results are based on yearly data from 2015-2017.

Looking at the OSII score coefficient, we see that it is statistically not significant. Nevertheless, a higher score increases the probability of an higher OSII buffer. This is an important result and means that the regulatory authorities take the OSII score into account when they set the OSII buffer. However, in the third column of Table 2 the coefficients of the country dummies are completely different and reach from +4.727 to −24.187. It leads to an important question: How much does the country of an OSII matters for the OSII buffer? The size of the country dummies already indicate that it might be more important than the OSII score.

As the coefficients of an ordered probit model do not allow to answer this question directly without translating these coefficients into probabilities, we calculate the probabilities of each country to set the OSII-buffer rate on the different levels from 0.25% to 1.5% given that the institution has a score of 1500. The results are shown in Figure 2.

The upper left graph in Figure 2 shows that only a few countries would assign an OSII buffer of at least 1.5% to a bank with an OSII score of 1500. For many countries the results (based on the coefficients in Table 2) suggest that many countries would set a OSII buffer of at least 1.5% with very low to zero probability. Notable exceptions are SE, IS, AT, NL, EE, HR, MT, RO, DE, LT and BE.

The upper right graph in Figure 2 shows that already more countries would assign an OSII buffer of at least 1% to a bank with an OSII score of 1500. However, countries like SI, ES, IT, CZ, DK and UK still assign a very low to zero probability. The lower left graph in Figure 2 presents similar probabilities as in the upper right graph. Finally, the lower right graph identifies those countries such as CZ, DK and UK that do not assign OSII buffers at all as described in Section 2.

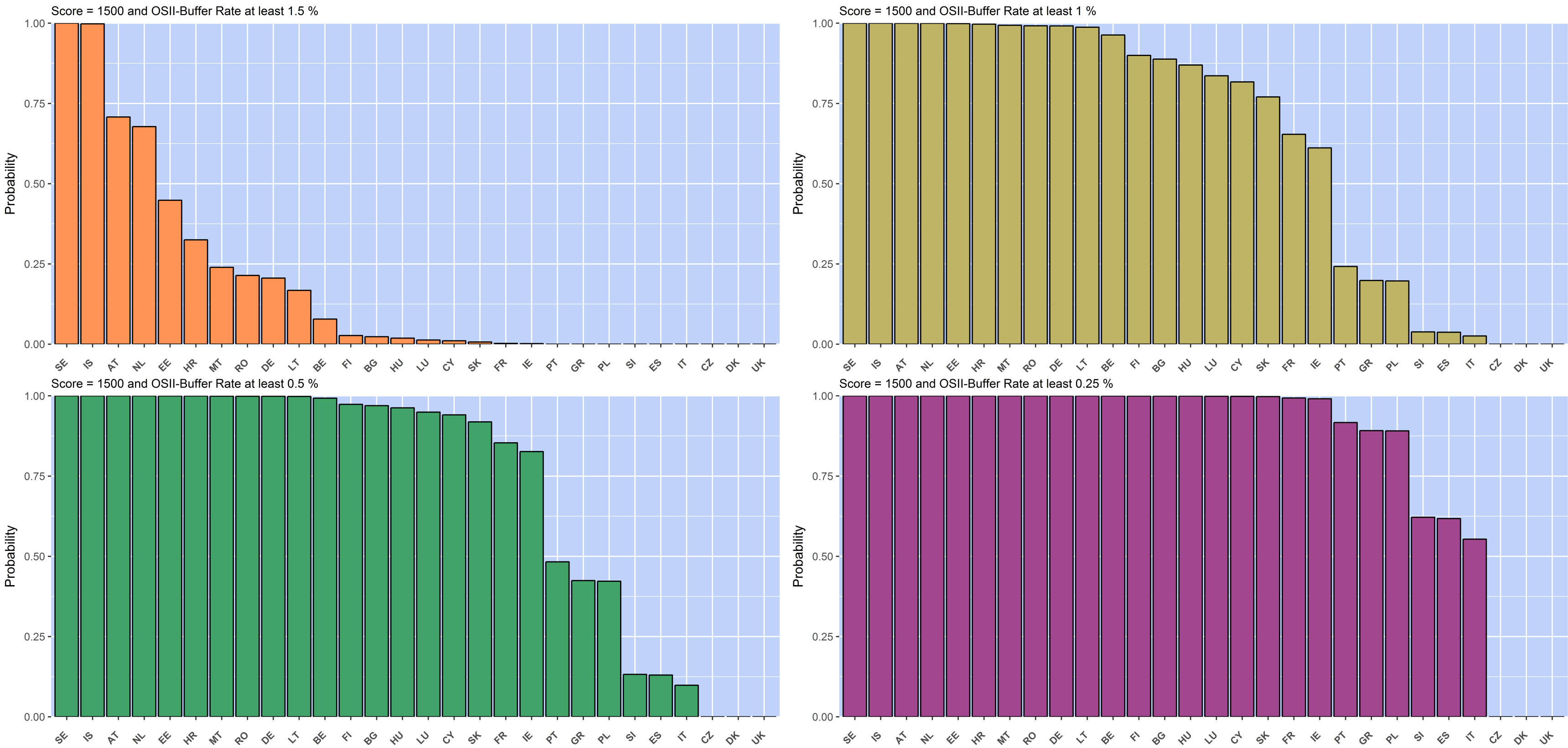
Overall Figure 2 gives a very good impression, how differently regulatory authorities in the European union assign OSII buffers to their respective banks even if the OSII scores are similar. In line with industry intuition, how much buffer an institution is attributed, does not only depend on the institutions' OSII score, but also depends - and even more strongly - on the local regulator. So, in order to create a level playing field one should prescribe minimal requirements on OSII buffers based on specific OSII scores. Obviously, financial stability would benefit from a race to the top (all countries apply the most prudent translation process) than from a race to the bottom.

### *6.2. Capital Requirement Scheme Simulation*

In this subsection, we make a cross-country comparison based on the following capital requirement scheme simulation: We predict the OSII buffers for each bank of the sample based on the model of Germany which is shown in Appendix A.[10] To predict the OSII buffer of bank $i$ in country $j$, we multiply its score by 0.0004 (see Table A.5) and add the Germany country dummy (1.38 − 0.3074). Then, we

[10] Our count data estimation results fit with equidispersion. It means that the mean and the variance are equal. The test statistic is calculated with the code of Kleiber and Zeileis (2008) and gives a value of −0.85 with a p-value of 0.8 which gives no indication of rejecting the null hypothesis of equidispersion. Therefore we do not need to consider another distribution (e.g. negative binomial distribution).

Figure 2: Estimated probability of certain OSII buffer conditional on an OSII Score of 1500.




Source: Own calculations.
The estimated probabilities are based on the results of Eq. (11) presented in Table 2.
The graph shows the conditional probability that a bank with an OSII score of 1500 in a specific country receives an OSII buffer of 1.5%, 1%, 0.5% and 0.25%.

assume that all banks have to increase or decrease their capital requirements by the calculated OSII buffer, even if a bank holds more capital than the "new" regulatory requirement. It could be that some banks have a CET1 ratio far beyond the requirements of Basel III, even with the additional OSII buffer requirements. However, there is a new draft by the European Parliament that suggests to sum the OSII buffer and the SyRB, instead of applying only the higher of the two.[11] If this change in legislation was accepted our capital requirement scheme simulation would be even more relevant, as for most of the 186 banks the SyRB is as least as high as the OSII buffer.

Figure 3 shows the capital requirement for each country cumulated in absolute values. The simulation reflects the case where each European bank would copy the German OSII buffer setting by their authorities. In nine countries the capital requirements for the banks would be above one billion Euro. The banks of UK would be most affected. The UK, Czech and Danish banks would have to increase their CET 1 capital by approximately 20 billion Euro. The only two countries in which the banks have capital surplus larger than 1 billion Euro on CET 1 in comparison to Germany are Sweden and Austria. Based on this simulation, the regulatory capital minimum of European banks would increase by 82.3 billion Euro. In some major EU member state countries, if the German OSII translation process was applied, this would even leave some prominent banks undercapitalized. Consequently, one could ask if some regulators award buffers on the basis of banks' capabilities rather than banks' systemic risk profile.

In Table 3 we report the largest banks in absolute values with capital requirements and capital surplus. The largest capital requirements would be in UK, DK and CZ. However due to their high CET1 ratios the Danish and Czech banks would not be really affected by an increase in the CET1 ratio. Based on our data 5 out of 10 banks in the Table 3 have a lower CET1 ratio than the European mean. So in the case of an increase of the OSII-buffer rate, this banks could be affected.

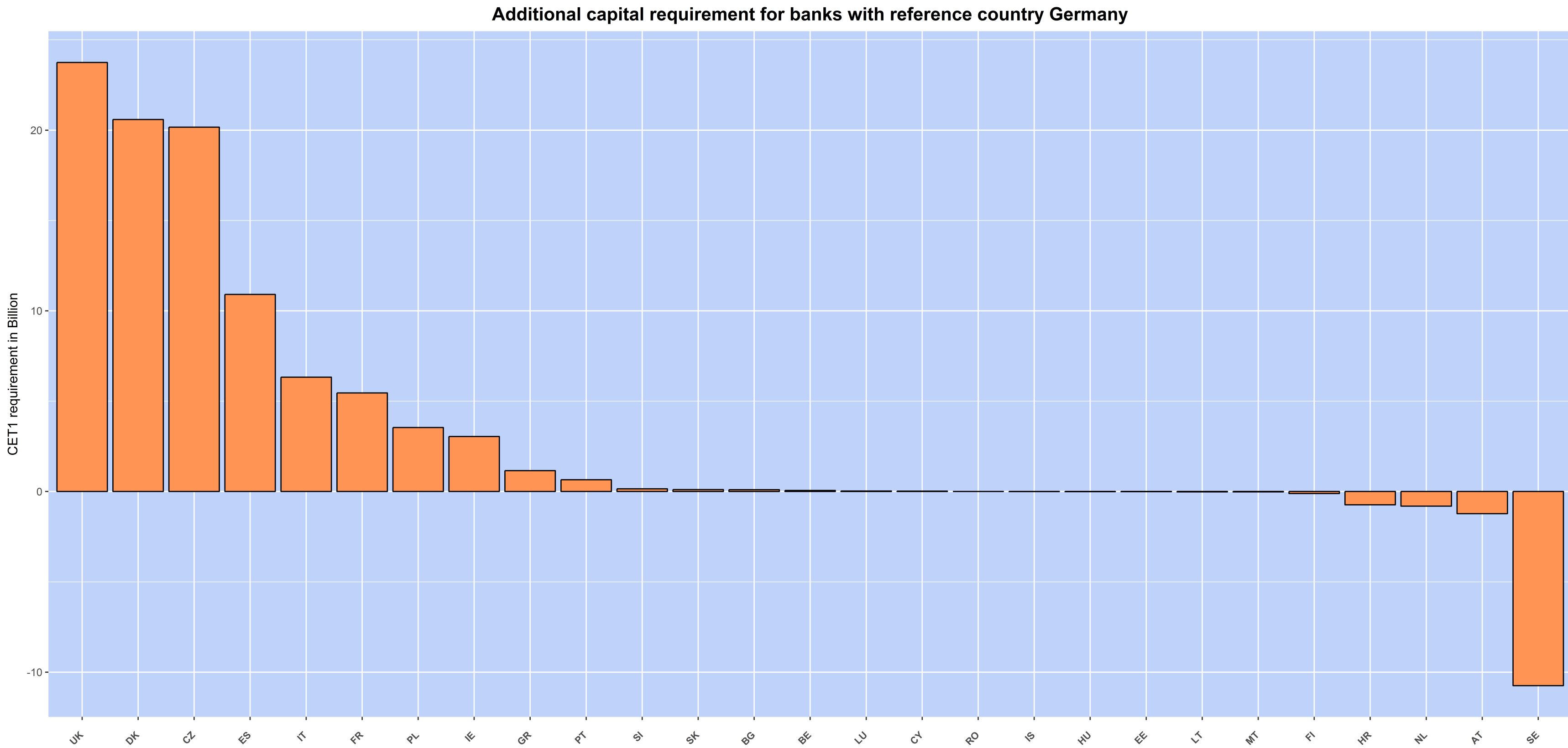
Table 3: Simulation of largest capital requirements and surplus by banks

| Bank | Country | Capital requirement | CET1 ratio | Bank | Country | Capital surplus | CET1 ratio |
|---|---|---|---|---|---|---|---|
| Dankse Bank | DK | 16.30 | 16.28% | SEB | SE | -4.28 | 18.84% |
| HSBC | UK | 10.71 | 13.60% | Svenska AB | SE | -3.55 | 21.25% |
| Ceska sporitelna | CZ | 6.97 | 16.64% | Swedbank | SE | -2.92 | 24.14% |
| CSOB | CZ | 6.03 | 17.18% | ABN Amro | NL | -0.78 | 17.06% |
| Santander | ES | 5.88 | 12.53% | Erste Group | AT | -0.51 | 13.36% |
| Komercni banka | CZ | 5.31 | 18.02% | RBI | AT | -0.45 | 13.88% |
| Unicredit S.p.A | IT | 3.87 | 8.15% | Raiffeisen Austria | HR | -0.23 | 16.93% |
| Barclays | UK | 3.66 | 12.36% | Zagrebacka | HR | -0.19 | 21.60% |
| BBVA | ES | 2.92 | 12.18% | Unicredit Austria | AT | -0.18 | 18.05% |
| Citi | IE | 2.92 | 14.35% | Splitska Banka | HR | -0.16 | 19.91% |

This table shows the 10 largest banks with CET1 requirements (left table) and the CET1 surplus (right table) according to a higher OSII buffer. The reference country is Germany and the values of the table are predicted via the Poisson estimation results (see Table A.5). The capital requirement and surplus is in Billion Euro. The mean CET1 ratio of European banks was 13.78% in 2016.

[11] See http://www.europarl.europa.eu/sides/getDoc.do?pubRef=-%2f%2fEP%2f%2fTEXT%2bREPORT%2bA8-2018-0243%2b0%2bDOC%2bXML%2bV0%2f%2fEN&language=EN for more details.

Figure 3: Simulation: Additional capital requirements for banks with reference country Germany




The graph show the capital requirements and surpluses which is cumulated over all banks in a country in reference to the German OSII buffer estimations. The capital requirements are calculated via the Poisson estimation.

### *6.3. A deeper look into the OSII buffer assignment*

After establishing a high degree of country heterogeneity in the OSII buffer assignment in Table 3 and A.5, we turn to the estimation of the Nash Bargaining outcome of Eq. 6. In Table 4, we present our results. In column 1, we estimate a version of the Nash bargaining solution. In column 2, we regress the OSII buffer only on OSII score and the country dummies. With this approach, we are first able to demonstrate that the OLS results (column 2) are very similar to the ordered probit (Table 3) and poisson count data model (Table A.5). If we compare column 1 to column 2, we see a reduction in the number of significant country dummies and also a reduction in size of most country dummy coefficients. We also demonstrate that the Target SyRB is part of the OSII buffer assignment process. If there is a target SyRB buffer in place, this improves the bargaining position of the regulator with respect to the banks' representatives. However, although the country heterogeneity is reduced, the target SyRB is itself determined by a bargaining process for each bank between the same or similar negotiators. The importance of the target SyRB also reduces the size of the OSII score coefficient by around two-third.

In the second column of Table 4, we assign the dummy variable "Mapru by Central Bank" to all countries, where the central bank has the leading role in the macroprudential regulation and consequently writes the first draft of the legal opinion on the OSII buffer assignment.[12] The coefficient of this Mapru dummy is positive and significant. The central bank as the leading macroprudential regulator would assign a 0.5pp higher OSII buffer than a non-central bank regulator for the same bank. This significant difference in the OSII buffer assignment could be attributed a generally higher risk aversion or to the independence of the central bank which would strengthen its bargaining power.

Finally, we control for the tier 1 ratio, regulatory quality and operating income divided by total assets. These variables have the expected positive sign but are not significant. A higher tier 1 ratio ceteris paribus reduces the probability that a OSII buffer is binding. A higher operating income enables banks to generate more tier 1 capital without issuing new shares or similar instruments.

[12] This group of countries includes BE, CZ, EE, IE, GR, FR, CY, LT, HU, MT, NL, PT, RO, SK, FI, SE and additionally AT, DE, BG, LV and SI.

Table 4: Estimation Results Nash Bargaining Solution

| | Nash Bargaining Countries | Nash Bargaining Mapru by CB | OLS with Country Dummies |
|---|---|---|---|
| (Intercept) | 0.4738 | $-0.5225^{**}$ | $1.1558^{***}$ |
| | (0.6061) | (0.1924) | (0.0879) |
| Score | $0.0114^{***}$ | $0.0304^{***}$ | $0.0320^{***}$ |
| | (0.0031) | (0.0035) | (0.0026) |
| Target SRB | $0.5055^{***}$ | $0.1544^{***}$ | |
| | (0.0556) | (0.0346) | |
| Tier1ratio (-1) | 0.0032 | 0.0028 | |
| | (0.0022) | (0.0035) | |
| Regulatory Quality (-1) | 0.0473 | $0.2481^{**}$ | |
| | (0.4111) | (0.0867) | |
| Operating Income Ratio (-1) | 0.0099 | 0.0515 | |
| | (0.0228) | (0.0324) | |
| Mapru by Central Bank | | $0.4723^{***}$ | |
| | | (0.0789) | |
| BE | −0.2034 | | $-0.4315^{***}$ |
| | (0.1128) | | (0.1066) |
| BG | $-1.8496^{***}$ | | $-0.6640^{***}$ |
| | (0.3836) | | (0.1320) |
| CY | −0.2729 | | $-0.5838^{**}$ |
| | (0.2170) | | (0.1866) |
| CZ | $-1.4696^{***}$ | | $-1.4544^{***}$ |
| | (0.2131) | | (0.1445) |
| DE | −0.2443 | | $-0.4191^{***}$ |
| | (0.1668) | | (0.1032) |
| DK | $-1.7277^{***}$ | | $-1.6962^{***}$ |
| | (0.1798) | | (0.1546) |
| EE | $-0.5054^{**}$ | | 0.0296 |
| | (0.1901) | | (0.1711) |
| ES | $-0.5176^{*}$ | | $-1.1529^{***}$ |
| | (0.2526) | | (0.1243) |
| FI | −0.2078 | | −0.3990 |
| | (0.2434) | | (0.2209) |
| FR | −0.3248 | | $-0.7444^{***}$ |
| | (0.1773) | | (0.1278) |
| GR | −0.3580 | | $-0.9721^{***}$ |
| | (0.5081) | | (0.1494) |
| HR | −0.6653 | | $-0.2725^{*}$ |
| | (0.4484) | | (0.1374) |
| HU | −0.3274 | | $-0.6627^{***}$ |
| | (0.3608) | | (0.1542) |
| IE | $-0.4769^{*}$ | | $-0.8523^{***}$ |
| | (0.1881) | | (0.1237) |
| IS | $-1.5134^{***}$ | | −0.0801 |
| | (0.2258) | | (0.1923) |
| IT | −0.4888 | | $-1.1782^{***}$ |
| | (0.3239) | | (0.1471) |
| LT | 0.0286 | | −0.1442 |
| | (0.2205) | | (0.2267) |
| LU | −0.1773 | | $-0.7510^{***}$ |
| | (0.2282) | | (0.2215) |
| MT | −0.0708 | | −0.2210 |
| | (0.2077) | | (0.1865) |
| NL | −0.2642 | | −0.1898 |
| | (0.2392) | | (0.2276) |
| PL | $-2.0497^{***}$ | | $-1.0559^{***}$ |
| | (0.2417) | | (0.1281) |
| PT | −0.4415 | | $-0.9977^{***}$ |
| | (0.2774) | | (0.1538) |
| RO | −0.1987 | | $-0.4199^{***}$ |
| | (0.3527) | | (0.1121) |
| SE | −0.4075 | | 0.1531 |
| | (0.2210) | | (0.1691) |
| SI | −0.5652 | | $-1.1643^{***}$ |
| | (0.3503) | | (0.1539) |
| SK | $-0.5751^{*}$ | | $-0.7012^{***}$ |
| | (0.2581) | | (0.1669) |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
This table shows the results of estimating Eq. (11). In all columns the dependent variable is the OSII buffer.
The table shows the estimated coefficients, t-statistics, McFadden $R^2$ and the number of observations.
CumHigh Oprobit Column: The independent variables is the EBA-score and the two dummy variables Higher SyRB and Cum SyRB.
Ordered Probit Column: The independent variable is the EBA-score (Score). The Threshold variables are the intercepts for each ordinal
Ordered Probit with Country Dummies: In addition to the EBA-Score, we also include a dummy for each country in the sample. The reference country is Austria.
The goodness of fit is calculated via the McFadden $R^2$ described in Eq. (12). The different intercepts denotes the intercept for each OSII buffer. The results are based on yearly data from 2015-2017.

## 7. Conclusion

In this paper, we present a first empirical analysis of how European union member states calibrate their buffer rates for other systemically important institutions. Given the fact that the identification of OSIIs via the OSII score calculation is based on the unified approach by EBA (2014) (see Table 1) our results on the OSII buffer calibration are quite surprising. They are very different across countries. Although the OSII score has the expected positive coefficient, implying that on average banks with a higher OSII score receive a higher OSII buffer, the country specific dummies are more important.[13] It shows that there is probably a missing link in the recommendation by EBA (2014) of how to translate the OSII score into the OSII buffer.

Our analysis reveals that each country in the European union judges the risks to financial stability stemming from the failure of an OSII quite differently. Alternatively, one could speculate on other motives, which would cause a national regulator to assign a lower buffer than prudent countries would have assigned. Obviously, financial stability would benefit from a race to the top (all countries apply the most prudent translation process) than from a race to the bottom. Given the advancement in macroprudential regulation to address the too big too fail dilemma since the financial crisis, it is about time to apply these measures and hopefully prevent bank support packages paid by the tax payer during the next crisis. In this context, we also suggest to follow the recommendation byESRB (2011a) that the national central bank should have a leading role in macro-prudential oversight.

As the OSII buffer is designed to address this risk ("caused losses"), we would suggest to quantify the risk more directly as suggested by Siebenbrunner et al. (2017). In their model different contagion losses are calculated based on the interbank network in Austria. After quantifying contagion losses based on the hypothetical failure of an OSII, a prudent regulator would then look at the relationship between capital ratios and probability of a bank failure and calibrate the OSII buffer accordingly. In case that the interbank network of banks is not available, Siebenbrunner et al. (2017) also confirm that the variables in the scoring approach by EBA (2014) are still very useful to predict contagion losses as a second best option.

Finally, we make a case for a unified scoring and translation process across all countries to ensure a level playing field for all OSIIs in the European union.

## References

Acemoglu, D., Ozdaglar, A. E., and Tahbaz-Salehi, A. (2015). Systemic risk in endogenous financial networks.

[13] We test the robustness of our results by estimating four different models (order probit model, count data model with Poisson distribution, quantile regression and OLS).

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2010). Measuring systemic risk. Working Paper 1002, Federal Reserve Bank of Cleveland.

Adrian, T. and Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, 106(7):1705–1741.

BIS (2012). A framework for dealing with domestic systemically important banks. Basel committee on banking supervision publication, Basel Committee on Banking Supervision.

BIS (2013). Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement. Basel committee on banking supervision publication, Basel Committee on Banking Supervision.

Brownlees, C. and Engle, R. F. (2016). Srisk: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, 30(1):48–79.

Cameron, C. and Trivedi, P. (2005). *Microeconometrics: Methods and Applications*. Camebridge University Press.

Carroll, N. (2017). *oglmx: Estimation of Ordered Generalized Linear Models*. R package version 2.0.0.3.

Dumontaux, N. and Pop, A. (2013). Understanding the market reaction to shockwaves: Evidence from the failure of lehman brothers. *Journal of Financial Stability*, 9(3):269–286.

EBA (2014). On the criteria to determine the conditions of application of Article 131(3) of Directive 2013/36/EU (CRD) in relation to the assessment of other systemically important institutions (O-SIIs). Eba guideline, European Banking Authority.

ECB (December 2009). European Central Bank. *Financial Stability Review*.

Eisenberg, L. and Noe, T. H. (2001). Risk in Financial Systems. *Management Science*, 47(2):236–249.

Engle, R., Jondeau, E., and Rockinger, M. (2014). Systemic risk in europe. *Review of Finance*, 19(1):145–190.

ESRB (2011a). Recommendation of the european systemic risk board of 21 september 2011 on lending in foreign currencies. Technical Report ESRB/2011/1, European Systemic Risk Board. Frankfurt.

ESRB (2011b). Recommendation of the european systemic risk board of 22 december 2011 on the macro-prudential mandate of national authorities. Technical Report ESRB/2011/3, European Systemic Risk Board. Frankfurt.

FED (2015). Calibrating the GSIB Surcharge. Fed publication, Board of Governors of the Federal Reserve System.

Harrell, F. E. (2018). *rms: Regression Modeling Strategies*. R package version 5.1-2.

Iori, G., Jafarey, S., and Padilla, F. G. (2006). Systemic risk on the interbank market. *Journal of Economic Behavior and Organization*, 61(4):525–542.

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2011). The worldwide governance indicators: methodology and analytical issues. *Hague Journal on the Rule of Law*, 3(2):220–246.

Kleiber, K. and Zeileis, A. (2008). *Applied Econometrics with R*. Springer-Verlag, New York. ISBN 978-0-387-77316-2.

Nash, J. (1953). Two-person cooperative games. *Econometrica: Journal of the Econometric Society*, pages 128–140.

Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT press.

Rime, B. (2001). Capital requirements and bank behaviour: Empirical evidence for switzerland. *Journal of Banking & Finance*, 25(4):789–805.

Siebenbrunner, C. and Sigmund, M. (2018a). An application of quantile panel estimation to systemic risk. Working paper.

Siebenbrunner, C. and Sigmund, M. (2018b). Do interbank markets price systemic risk? Working Paper.

Siebenbrunner, C., Sigmund, M., and Kerbl, S. (2017). Can bank-specific variables predict contagion effects? *Quantitative Finance*, 17(12):1805–1832.

Venables, W. N. and Ripley, B. D. (2002). *Modern Applied Statistics with S*. Springer, New York, fourth edition. ISBN 0-387-95457-0.

Wheelock, D. and Wilson, P. (2000). Why do banks disappear? the determinants of u.s. bank failures and acquisitions. *The Review of Economics and Statistics*, 82(1):127–138.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press, Cambridge, MA.

## Appendix A. OLS and Poisson estimation results

In this section, we present our estimation results for the count data models and the OLS models. In Table A.5, we present four models: (1) the count data model with the Poisson distribution, where only the OSII Score is added as explanatory variable, (2) the count data model with the Poisson distribution and country dummies, (3) the OLS model with only the OSII score and (4) the OLS model with country dummies.

As in Table 2, the score has again a positive influence on the OSII buffer, the higher the score the higher the buffer. As we see in Table A.5, the count data estimation and the OLS estimation without country dummies perform relatively poor ($R^2$ of 0.24 and respectively 0.33) with respect to the models with country dummies ($R^2$ of 0.86 and respectively 0.82).

Overall, we show that the country dummy variables have a strong impact on the OSII buffer. Our results suggest that the regulatory authority has a stronger influence on the OSII buffer than the OSII score. We also confirm the results in Section 6.1.

Table A.5: Target O-SII Buffer: Possion Count Data and OLS Estimation

| | Poisson | Poisson dummy | OLS | OLS dummy |
|---|---|---|---|---|
| Intercept | 0.6933*** | 1.3800*** | 0.3943*** | 1.1399*** |
| | (0.0547) | (0.1276) | (0.0472) | (0.0835) |
| Score | 0.0004*** | 0.0004*** | 0.0004*** | 0.0003*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| BE | | −0.3412* | | −0.4127*** |
| | | (0.1523) | | (0.0983) |
| BG | | −0.5533* | | −0.6420*** |
| | | (0.2153) | | (0.1191) |
| CY | | −0.4974* | | −0.5798*** |
| | | (0.2296) | | (0.1394) |
| CZ | | −21.0707 | | −1.5082*** |
| | | (3530.1009) | | (0.1322) |
| DE | | −0.3074* | | −0.4037*** |
| | | (0.1561) | | (0.0968) |
| DK | | −21.2388 | | −1.6508*** |
| | | (3509.2569) | | (0.1393) |
| EE | | −0.2224 | | −0.0852 |
| | | (0.2089) | | (0.1500) |
| ES | | −1.3692*** | | −1.1489*** |
| | | (0.2506) | | (0.1163) |
| FI | | −0.4285 | | −0.5202** |
| | | (0.2764) | | (0.1605) |
| FR | | −0.6602*** | | −0.7407*** |
| | | (0.1946) | | (0.1137) |
| GR | | −0.8726*** | | −0.9675*** |
| | | (0.2180) | | (0.1304) |
| HR | | −0.0610 | | −0.0777 |
| | | (0.1830) | | (0.1226) |
| HU | | −0.5426* | | −0.6186*** |
| | | (0.2289) | | (0.1270) |
| IE | | −0.6781*** | | −0.7398*** |
| | | (0.2006) | | (0.1113) |
| IS | | −0.3157 | | −0.1068 |
| | | (0.2439) | | (0.1836) |
| IT | | −1.2745*** | | −1.1696*** |
| | | (0.2740) | | (0.1334) |
| LT | | −0.3986 | | −0.2570 |
| | | (0.2369) | | (0.1624) |
| LU | | −0.7934* | | −0.7415*** |
| | | (0.3745) | | (0.1614) |
| MT | | −0.1887 | | −0.2235 |
| | | (0.2765) | | (0.1795) |
| NL | | −0.2527 | | −0.1260 |
| | | (0.2169) | | (0.1487) |
| PL | | −1.2700*** | | −1.0043*** |
| | | (0.2705) | | (0.1139) |
| PT | | −1.0180*** | | −0.9958*** |
| | | (0.2922) | | (0.1391) |
| RO | | −0.2933 | | −0.4129*** |
| | | (0.1651) | | (0.1027) |
| SE | | −0.1680 | | 0.1371 |
| | | (0.2206) | | (0.1622) |
| SI | | −1.4600*** | | −1.1515*** |
| | | (0.3375) | | (0.1322) |
| SK | | −0.6045* | | −0.7058*** |
| | | (0.2637) | | (0.1481) |
| UK | | −20.8473 | | −1.2961*** |
| | | (1658.4126) | | (0.0950) |
| Pseudo R-Squared | 0.2425 | 0.8621 | | |
| R-Squared | | | 0.3357 | 0.8248 |
| Num. Obs. | 274 | 274 | 274 | 274 |

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
This table shows the results of estimating Eq. (15) and the OLS estimation. The table shows the estimated coefficients, t-statistics, McFadden $R^2$, adjusted $R^2$ and the number of observations. The dependent variables is the EBA-score (Score). In the Poisson dummy and OLS dummy equation, country dummy variables are added to the model. In case of the Poisson estimation, the goodness of fit is calculated via the McFadden $R^2$ described in Eq. 17. For the OLS model we take the adjusted $R^2$. The results are based on yearly data from 2015-2017.

In Table A.6 and Table A.7, we make a cross country comparison of the OSII buffer translation. We take the largest bank in each European union member state and use the OLS estimation result in Table A.5 to assign the OSII buffer hypothetically in each country. In particular, the off-diagonal values show what OSII buffer would be assigned to a bank, if it was under a different macroprudential regulation.

The results are in line with Table 3 and quantify the extend of heterogeneity in the buffer attribution between countries based on the largest bank in each country respectively.

Table A.6: OLS prediction of a bank's OSII buffer in different countries

| | AT | BE | BG | CY | CZ | DE | DK | EE | ES | FI | FR | GR | HR | HU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Erste Group | 1.91 | 1.56 | 1.19 | 1.40 | 0.38 | 1.56 | 0.24 | 1.85 | 0.83 | 1.45 | 1.23 | 1.01 | 1.78 | 1.35 |
| BNP BE | 1.94 | 1.59 | 1.22 | 1.42 | 0.41 | 1.59 | 0.27 | 1.88 | 0.85 | 1.48 | 1.26 | 1.04 | 1.81 | 1.38 |
| UC Bulbank | 1.87 | 1.52 | 1.15 | 1.36 | 0.35 | 1.53 | 0.21 | 1.81 | 0.79 | 1.42 | 1.20 | 0.98 | 1.74 | 1.32 |
| BOC | 2.01 | 1.66 | 1.29 | 1.50 | 0.49 | 1.67 | 0.34 | 1.95 | 0.93 | 1.55 | 1.33 | 1.12 | 1.88 | 1.45 |
| CSOB | 1.91 | 1.57 | 1.19 | 1.40 | 0.39 | 1.57 | 0.25 | 1.85 | 0.83 | 1.46 | 1.24 | 1.02 | 1.78 | 1.36 |
| DB | 2.02 | 1.67 | 1.30 | 1.51 | 0.50 | 1.68 | 0.35 | 1.96 | 0.94 | 1.56 | 1.34 | 1.13 | 1.89 | 1.46 |
| Dankse Bank | 2.86 | 2.51 | 2.13 | 2.34 | 1.33 | 2.51 | 1.19 | 2.79 | 1.77 | 2.40 | 2.18 | 1.96 | 2.72 | 2.30 |
| Swedbank | 2.13 | 1.78 | 1.41 | 1.61 | 0.60 | 1.78 | 0.46 | 2.07 | 1.04 | 1.67 | 1.45 | 1.23 | 2.00 | 1.57 |
| Santander | 2.44 | 2.09 | 1.71 | 1.92 | 0.91 | 2.09 | 0.77 | 2.37 | 1.35 | 1.98 | 1.76 | 1.54 | 2.30 | 1.88 |
| OP Group | 1.87 | 1.52 | 1.15 | 1.36 | 0.35 | 1.53 | 0.20 | 1.81 | 0.79 | 1.41 | 1.19 | 0.98 | 1.74 | 1.31 |
| BNP FR | 1.90 | 1.55 | 1.18 | 1.38 | 0.37 | 1.55 | 0.23 | 1.83 | 0.81 | 1.44 | 1.22 | 1.00 | 1.76 | 1.34 |
| BOG | 2.21 | 1.86 | 1.48 | 1.69 | 0.68 | 1.86 | 0.54 | 2.14 | 1.12 | 1.75 | 1.53 | 1.31 | 2.07 | 1.65 |
| Zagrebacka | 2.09 | 1.74 | 1.37 | 1.57 | 0.56 | 1.74 | 0.42 | 2.03 | 1.00 | 1.63 | 1.41 | 1.19 | 1.96 | 1.53 |
| OTP HU | 1.96 | 1.62 | 1.24 | 1.45 | 0.44 | 1.62 | 0.30 | 1.90 | 0.88 | 1.51 | 1.29 | 1.07 | 1.83 | 1.41 |
| BOI | 1.81 | 1.46 | 1.09 | 1.30 | 0.29 | 1.47 | 0.14 | 1.75 | 0.73 | 1.35 | 1.13 | 0.92 | 1.68 | 1.25 |
| Arion bank | 2.23 | 1.88 | 1.51 | 1.72 | 0.71 | 1.89 | 0.57 | 2.17 | 1.15 | 1.77 | 1.56 | 1.34 | 2.10 | 1.67 |
| Unicredit | 2.35 | 2.00 | 1.62 | 1.83 | 0.82 | 2.00 | 0.68 | 2.28 | 1.26 | 1.89 | 1.67 | 1.45 | 2.21 | 1.79 |
| AB SEB bank | 2.49 | 2.14 | 1.77 | 1.98 | 0.96 | 2.14 | 0.82 | 2.43 | 1.41 | 2.03 | 1.81 | 1.59 | 2.36 | 1.93 |
| Clearstream | 1.19 | 0.84 | 0.47 | 0.67 | -0.34 | 0.84 | -0.48 | 1.13 | 0.10 | 0.73 | 0.51 | 0.29 | 1.06 | 0.63 |
| BOV | 1.88 | 1.53 | 1.15 | 1.36 | 0.35 | 1.53 | 0.21 | 1.81 | 0.79 | 1.42 | 1.20 | 0.98 | 1.74 | 1.32 |
| ING Bank NL | 2.48 | 2.13 | 1.76 | 1.97 | 0.95 | 2.13 | 0.81 | 2.42 | 1.40 | 2.02 | 1.80 | 1.58 | 2.35 | 1.92 |
| PKO BP | 1.67 | 1.32 | 0.95 | 1.16 | 0.15 | 1.33 | 0.01 | 1.61 | 0.59 | 1.22 | 1.00 | 0.78 | 1.54 | 1.12 |
| Caixa | 1.89 | 1.54 | 1.17 | 1.37 | 0.36 | 1.54 | 0.22 | 1.83 | 0.80 | 1.43 | 1.21 | 0.99 | 1.76 | 1.33 |
| BCR | 1.67 | 1.32 | 0.95 | 1.15 | 0.14 | 1.32 | 0.00 | 1.61 | 0.58 | 1.21 | 0.99 | 0.77 | 1.54 | 1.11 |
| Nordea | 2.64 | 2.29 | 1.92 | 2.12 | 1.11 | 2.29 | 0.97 | 2.58 | 1.55 | 2.18 | 1.96 | 1.74 | 2.51 | 2.08 |
| NLB SI | 2.09 | 1.74 | 1.37 | 1.58 | 0.57 | 1.75 | 0.43 | 2.03 | 1.01 | 1.63 | 1.42 | 1.20 | 1.96 | 1.53 |
| VUB | 1.84 | 1.49 | 1.12 | 1.32 | 0.31 | 1.49 | 0.17 | 1.78 | 0.75 | 1.38 | 1.16 | 0.94 | 1.71 | 1.28 |
| HSBC | 1.60 | 1.26 | 0.88 | 1.09 | 0.08 | 1.26 | -0.06 | 1.54 | 0.52 | 1.15 | 0.93 | 0.71 | 1.47 | 1.05 |

Source OeNB. Own calculation.
In each row, we predict the (hypothetical) OSII buffer of the largest bank in a particular country (e.g. Erste Group) based on the estimation results in Table A.5 in column 4 (OLS dummy). In the diagonal elements, the OSII buffer of a bank in its home country is predicted (e.g. Erste Group in AT). In the off-diagonal elements, the hypothetical prediction of a particular bank for all other European union member states is calculated (e.g. Erste Group in BE, BG, ect.).

Table A.7: OLS prediction of bank's OSII buffer in different countries

| | IE | IS | IT | LT | LU | MT | NL | PL | PT | RO | SE | SI | SK | UK |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Erste Group | 1.23 | 1.74 | 0.81 | 1.72 | 1.23 | 1.75 | 1.79 | 0.83 | 0.98 | 1.56 | 1.98 | 0.82 | 1.24 | 0.67 |
| BNP BE | 1.26 | 1.77 | 0.84 | 1.75 | 1.25 | 1.78 | 1.82 | 0.85 | 1.01 | 1.59 | 2.00 | 0.85 | 1.27 | 0.70 |
| UC Bulbank | 1.20 | 1.70 | 0.77 | 1.69 | 1.19 | 1.71 | 1.76 | 0.79 | 0.94 | 1.52 | 1.94 | 0.78 | 1.20 | 0.64 |
| BOC | 1.33 | 1.84 | 0.91 | 1.82 | 1.33 | 1.85 | 1.90 | 0.93 | 1.08 | 1.66 | 2.08 | 0.92 | 1.34 | 0.77 |
| CSOB | 1.24 | 1.74 | 0.81 | 1.73 | 1.23 | 1.75 | 1.80 | 0.83 | 0.98 | 1.56 | 1.98 | 0.83 | 1.25 | 0.68 |
| DB | 1.34 | 1.85 | 0.92 | 1.83 | 1.34 | 1.86 | 1.91 | 0.94 | 1.09 | 1.67 | 2.09 | 0.93 | 1.35 | 0.78 |
| Dankse Bank | 2.18 | 2.68 | 1.75 | 2.67 | 2.17 | 2.69 | 2.74 | 1.77 | 1.92 | 2.50 | 2.92 | 1.77 | 2.19 | 1.62 |
| Swedbank | 1.45 | 1.96 | 1.03 | 1.94 | 1.44 | 1.97 | 2.01 | 1.04 | 1.20 | 1.78 | 2.20 | 1.04 | 1.46 | 0.89 |
| Santander | 1.76 | 2.26 | 1.33 | 2.25 | 1.75 | 2.28 | 2.32 | 1.35 | 1.50 | 2.08 | 2.50 | 1.35 | 1.77 | 1.20 |
| OP Group | 1.19 | 1.70 | 0.77 | 1.68 | 1.19 | 1.71 | 1.76 | 0.79 | 0.94 | 1.52 | 1.94 | 0.78 | 1.20 | 0.63 |
| BNP FR | 1.22 | 1.72 | 0.79 | 1.71 | 1.21 | 1.74 | 1.78 | 0.81 | 0.96 | 1.54 | 1.96 | 0.81 | 1.23 | 0.66 |
| BOG | 1.53 | 2.03 | 1.10 | 2.02 | 1.52 | 2.05 | 2.09 | 1.12 | 1.27 | 1.85 | 2.27 | 1.12 | 1.54 | 0.97 |
| Zagrebacka | 1.41 | 1.92 | 0.99 | 1.90 | 1.40 | 1.93 | 1.97 | 1.00 | 1.16 | 1.74 | 2.15 | 1.00 | 1.42 | 0.85 |
| OTP HU | 1.29 | 1.79 | 0.86 | 1.78 | 1.28 | 1.80 | 1.85 | 0.88 | 1.03 | 1.61 | 2.03 | 0.88 | 1.30 | 0.73 |
| BOI | 1.13 | 1.64 | 0.71 | 1.62 | 1.13 | 1.65 | 1.70 | 0.73 | 0.88 | 1.46 | 1.88 | 0.72 | 1.14 | 0.57 |
| Arion bank | 1.55 | 2.06 | 1.13 | 2.05 | 1.55 | 2.07 | 2.12 | 1.15 | 1.30 | 1.88 | 2.30 | 1.14 | 1.56 | 0.99 |
| Unicredit | 1.67 | 2.17 | 1.24 | 2.16 | 1.66 | 2.19 | 2.23 | 1.26 | 1.41 | 1.99 | 2.41 | 1.26 | 1.68 | 1.11 |
| AB SEB bank | 1.81 | 2.32 | 1.39 | 2.30 | 1.81 | 2.33 | 2.37 | 1.41 | 1.56 | 2.14 | 2.56 | 1.40 | 1.82 | 1.25 |
| Clearstream | 0.51 | 1.02 | 0.09 | 1.00 | 0.50 | 1.03 | 1.07 | 0.10 | 0.26 | 0.84 | 1.25 | 0.10 | 0.52 | -0.05 |
| BOV | 1.20 | 1.70 | 0.77 | 1.69 | 1.19 | 1.72 | 1.76 | 0.79 | 0.94 | 1.52 | 1.94 | 0.79 | 1.21 | 0.64 |
| ING Bank NL | 1.80 | 2.31 | 1.38 | 2.29 | 1.80 | 2.32 | 2.36 | 1.39 | 1.55 | 2.13 | 2.55 | 1.39 | 1.81 | 1.24 |
| PKO BP | 1.00 | 1.50 | 0.57 | 1.49 | 0.99 | 1.51 | 1.56 | 0.59 | 0.74 | 1.32 | 1.74 | 0.58 | 1.00 | 0.44 |
| Caixa | 1.21 | 1.72 | 0.79 | 1.70 | 1.20 | 1.73 | 1.77 | 0.80 | 0.96 | 1.54 | 1.96 | 0.80 | 1.22 | 0.65 |
| BCR | 0.99 | 1.49 | 0.57 | 1.48 | 0.98 | 1.51 | 1.55 | 0.58 | 0.74 | 1.31 | 1.73 | 0.58 | 1.00 | 0.43 |
| Nordea | 1.96 | 2.47 | 1.54 | 2.45 | 1.95 | 2.48 | 2.52 | 1.55 | 1.71 | 2.29 | 2.71 | 1.55 | 1.97 | 1.40 |
| NLB SI | 1.41 | 1.92 | 0.99 | 1.91 | 1.41 | 1.93 | 1.98 | 1.01 | 1.16 | 1.74 | 2.16 | 1.00 | 1.42 | 0.85 |
| VUB | 1.16 | 1.67 | 0.74 | 1.65 | 1.15 | 1.68 | 1.72 | 0.75 | 0.91 | 1.49 | 1.91 | 0.75 | 1.17 | 0.60 |
| HSBC | 0.93 | 1.43 | 0.50 | 1.42 | 0.92 | 1.44 | 1.49 | 0.52 | 0.67 | 1.25 | 1.67 | 0.52 | 0.94 | 0.37 |

See table notes under Table A.6

## Appendix B. OLS and Poisson estimation results with 186 banks

To provide further robustness checks, we re-estimate Table A.5 with only 186 banks, considering only the first OSII buffer decision for each OSII. Thus, each OSII enters the estimation only once. The results are almost identical. Therefore, the country heterogeneity in the OSII buffer assignment cannot be explained by the fact that some OSIIs have already received more than one OSII buffer decision in the last years.

Table B.8: Target O-SII Buffer: Possion Count Data and OLS Estimation

| | Poisson | Poisson dummy | OLS | OLS dummy |
|---|---|---|---|---|
| Intercept | 0.6849*** | 1.4032*** | 0.4085*** | 1.1542*** |
| | (0.0662) | (0.1765) | (0.0472) | (0.1295) |
| Score | 0.0004*** | 0.0003*** | 0.0004*** | 0.0003*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| BE | | −0.3350 | | −0.4080* |
| | | (0.2359) | | (0.1663) |
| BG | | −0.5582* | | −0.6432*** |
| | | (0.2456) | | (0.1592) |
| CY | | −0.4852 | | −0.5694** |
| | | (0.2584) | | (0.1783) |
| CZ | | −21.0717 | | −1.5051*** |
| | | (3534.1169) | | (0.1713) |
| DE | | −0.3398 | | −0.4306** |
| | | (0.2186) | | (0.1499) |
| DK | | −21.2310 | | −1.6409*** |
| | | (3551.8245) | | (0.1783) |
| EE | | −0.1595 | | 0.0570 |
| | | (0.3065) | | (0.2546) |
| ES | | −1.3488*** | | −1.1307*** |
| | | (0.3462) | | (0.1780) |
| FI | | −0.4247 | | −0.5165* |
| | | (0.3005) | | (0.1988) |
| FR | | −0.6524* | | −0.7333*** |
| | | (0.2750) | | (0.1781) |
| GR | | −0.8556** | | −0.9461*** |
| | | (0.3066) | | (0.2028) |
| HR | | −0.0579 | | −0.0752 |
| | | (0.2177) | | (0.1623) |
| HU | | −0.5440* | | −0.6191*** |
| | | (0.2575) | | (0.1664) |
| IE | | −0.7424** | | −0.7769*** |
| | | (0.2837) | | (0.1714) |
| IS | | −0.2806 | | −0.0754 |
| | | (0.2740) | | (0.2238) |
| IT | | −1.2455** | | −1.1862*** |
| | | (0.3969) | | (0.2201) |
| LT | | −0.3646 | | −0.2362 |
| | | (0.2672) | | (0.2014) |
| LU | | −0.8105* | | −0.7510*** |
| | | (0.3933) | | (0.2000) |
| MT | | −0.1818 | | −0.2181 |
| | | (0.3006) | | (0.2178) |
| NL | | −0.2279 | | −0.1126 |
| | | (0.2482) | | (0.1875) |
| PL | | −1.2790*** | | −1.0082*** |
| | | (0.2954) | | (0.1545) |
| PT | | −1.0120** | | −0.9893*** |
| | | (0.3151) | | (0.1779) |
| RO | | −0.2875 | | −0.4025* |
| | | (0.2305) | | (0.1593) |
| SE | | −0.1350 | | 0.1570 |
| | | (0.2526) | | (0.2012) |
| SI | | −1.4551*** | | −1.1483*** |
| | | (0.3575) | | (0.1713) |
| SK | | −0.5979* | | −0.6980*** |
| | | (0.2889) | | (0.1867) |
| UK | | −20.8636 | | −1.3053*** |
| | | (2346.6772) | | (0.1485) |
| Pseudo $R^2$ | 0.1167 | 0.4103 | | |
| Adjusted $R^2$ | | | 0.3264 | 0.8109 |
| Num. Obs. | 186 | 186 | 186 | 186 |

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
This table shows the results of estimating Eq. (15) and the OLS model but only with 186 observation. This table shows the estimated coefficients, t-statistics, McFadden $R^2$, adjusted $R^2$ and the number of observations. The dependent variables is the EBA-score (Score). In the Poisson dummy and OLS dummy equation, country dummy variables are added to the model. The goodness of fit is calculated via the McFadden $R^2$ described in Eq. 17. The results are based on yearly data from 2015-2017.

# Appendix C. Estimation results without CZ and DK

To be completed.