Macroprudential Regulation: A Risk Management Approach*

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Abstract

We develop a credit portfolio approach to measuring a Central Bank's exposure to systemic risk (multiple simultaneous defaults). We apply the model to a sample of European banks using CDS prices, which allows us to also cover non-listed banks. We then derive optimal macroprudential capital buffers based on individual banks' contributions to systemic risk in two steps. First we minimize aggregate systemic risk subject to an average capital buffer by allocating it across banks. Then we also endogenously set that average buffer by optimizing a welfare function balancing social costs and benefits of macroprudential buffers. We find substantial gaps between market-price based optimal buffers and macroprudential buffers as currently applied in our sample of European banks.

JEL codes: G01, G20, G18, G38

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1 Introduction

As of today, there exists very little theoretically backed guidance on how to calibrate macroprudential capital add-ons across banks. Recent academic approaches to measuring individual banks' contributions to systemic risk that could potentially resolve this gap have, unfortunately, not been used in practice either because their use of equity returns precludes inclusion of non-listed banks, or because regulators have been reluctant to use market data in building policy guidelines. In this paper we address each of these ambitions by introducing a structured credit portfolio model to assess a Central Bank's exposure to systemic risk; we next implement that model empirically using CDS prices so we can also cover non-listed banks. We map individual banks' contributions to systemic risk into bank-specific macroprudential buffers using an explicit optimization approach trading off the social costs of higher buffers (reduced lending) against the social benefits (reduced expected systemic losses in a systemic crisis). We apply our framework to a heterogeneous sample of listed and non-listed European systemic banks.

Regulators worldwide use macroprudential capital requirements as one of the key instruments to manage *ex-ante* the risks of a systemic crisis. Increasing the loss-absorbing capacity of large, economically important, interconnected banks reduces the chances of their default in adverse circumstances, and thus curtails the possibility that they can trigger cascading distress of related institutions. In a recent report, the ESRB sums up the ambitions and challenges ahead for regulators in using the instruments at their disposal:

> *The experience that has been gained with the application of macroprudential provisions in the last ten years highlights the need for more consistent, forward-looking and proactive countercyclical use of macroprudential instruments.*[1]

According to the regulatory frameworks in place, banks which are found to be domestically or globally systemically important (D-SIBs and G-SIBs respectively) are required

[1] Cf. ESRB (2021).

to maintain additional loss-absorbing capital buffer to the minimum requirement in order to mitigate the possible negative impact of their failure on the domestic or respectively the international financial systems.[2]

Focusing on a European sample of banks, however, we expose the heterogeneity with which national policymakers set the capital buffers that are at their discretion. The lack of consistent methodology makes it not only difficult to assess the adequacy of the buffers in any given country, but has also led to buffers of widely diverging stringency across countries within the Eurozone as each country applies the general guidelines differently. For want of a generally accepted basic framework, aligning these diverging approaches has proven to be difficult so far.

In the methodology currently in use by Central Banks, regulators adjust buffers for each bank considered until their estimated contribution to systemic risk equals the contribution of a presumably non-systemic reference bank and is therefore called the *Equal Expected Impact approach* (EEI).[3] But (even when based on market prices) the EEI approach suffers from a consistency problem similar to the problem highlighted by Gauthier et al. (2012): while macroprudential regulation is key in addressing risk spillovers from the banking sector, the regulator runs into a fixed point problem precisely because of these spillovers. In the context of the EEI approach, this implies that lowering the systemic contribution of a bank with high systemic scores to the level of the systemic risk contribution of a non-systemic reference bank or group of banks will in turn affect the contribution of that non-systemic bank as well. We tackle this problem, but not by iterating until the solutions converge to the fixed point problem as suggested by Gauthier et al. (2012), we address the problem more directly by defining an explicit welfare function incorporating the social costs and benefits of capital buffers. This allows us to derive optimal macroprudential buffers trading off the costs of reduced credit against the benefits of reduced expected shortfalls conditional on a systemic crisis by optimizing across the capital buffer requirements for all banks at the same time, while directly internalizing

[2] Regulatory framework is explored in more details in Section 2.2.
[3] Cf. FRB (2015); Passmore and von Hafften (2019); Jiron et al. (2021); Geiger et al. (2022).

the positive safety spillover externality highlighted by Gauthier et al. (2012).

There are several key mechanisms behind our approach. First, we introduce a structural credit model to relate the default risk of a single bank to its capital requirements using a framework similar to the well known Merton model describing equity as a call option (see Merton (1974)). This is used to imply the current vulnerability of a bank, as well as to inform about the potential reduction in risk if a bank has to satisfy higher buffer requirements. Second, the propensity of multiple banks to default at the same time determines the degree to which a bank's fragility is systemic in nature. We use time co-variation in the single-name CDS spreads of the underlying banks to estimate banks' common factor exposures driving the common variation in their creditworthiness. Our approach does not need granular data on the loan holdings of individual banks.

Our main innovation is based on extending this single bank credit risk model to a structural portfolio of risky and correlated credits and using it to estimate a Central Bank's exposure to systemic risk stemming from direct and indirect contributions from individual banks. We then map these contributions to optimally set macroprudential buffers by trading off the social costs of higher buffers (through reduced lending) against the social benefits of reduced expected systemic losses as higher buffers lead to the reduced default probabilities. The model and its empirical implementation using CDS prices allow us to base this approach fully on market information.

To introduce the model we first apply it to a less ambitious exercise building on the EEI approach through which supervisors currently aim at equalizing the expected default loss between systemic institutions and a non-systemic reference bank. In this approach, regulators use the systemic score that each bank gets as a crude measure of its social Loss Given Default (sLGD). By managing banks' probability of distress through setting buffer requirements, the expected losses of distress are equalized.[4] Using the same philosophy, we develop an alternative approach that is based on market prices and the size of banks' liabilities, rather than on regulatory scores.

[4]Cf. EBA (2020) for a brief overview of the approach and ESRB (2017) for an international comparison of its application in the EU. FRB (2015) provide a similar overview as it relates to the G-SII framework.

To that end, we develop a novel bank-specific measure of systemic importance based on implied default correlations, the Systemic Cost of Default (SCD). This measure quantifies the cost of distress of a financial institution beyond its expected default losses by also considering its tendency to default together with other institutions. We show that such a measure can be split into a microprudential and a macroprudential component. We demonstrate how addressing an individual bank's default risk through higher capital buffers not only lowers its own expected default costs, but also lowers the indirect systemic costs of other banks by lowering the potential that it may associate with other bank's concurrent default. We interpret this as a positive safety spillover effect from the introduction of macroprudential buffers. We show how using this new measure allows the application of the EEI approach to be fully based on information embedded in market prices. But we also illustrate that the resulting mapping from scores to buffers with the EEI approach depends on the reference institution chosen and the weight this institution gets assigned.

This shortcoming does not affect our main innovation, a full optimisation approach to setting macroprudential buffers trading of the marginal cost of reduced credit against the marginal benefits of reduced expected systemic losses when setting buffers. We implement this as a two-step optimization problem. In the first step, macroprudential capital buffer requirements are set for individual banks to minimize the Expected Shortfall (ES) subject to an average capital ratio for the sector as a whole. This first step is related to an idea proposed by Acharya et al. (2017) who refers to an average tax rate that can be allocated across systemic institutions to make them internalize the externality they pose on the financial system. We take this idea one step further by also showing how the average can be calibrated as well. In that second step we derive the target rate from a trade-off that results when banks' capital buffers are raised. On one hand, the higher loss-absorbing capacity in the system reduces the expected costs of financial distress. On the other, a higher capital requirement can induce output losses if it results in reduced availability of bank credit. It is up to a policymaker to find the optimum between the two effects.

This paper continues as follows: Section 2 discusses the relation of our study to the wider literature and then puts in the context of the current regulatory framework on bank capital buffers; Section 3 discusses the mechanics of the credit model behind our estimates of systemic risk, which allows us to go from observed CDS spreads to asset variance and systemic risk relations; Section 4 develops the credit default version of the EEI approach and presents empirical results using data on key European banks; Section 5 shows the risk optimization problem underpinning the process of regulating systemic risk and provides a cost and benefit approach to calibrate the aggregate level of macro buffers; and finally, Section 6 concludes.[5]

2 Relation to the Literature and the Policy Debate

2.1 Academic Literature

This paper is related to several disparate strands of the literature.

First of all, we build on existing studies that quantify systemic risk through asset price co-movements (Lehar, 2005; Huang et al., 2012; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017; Acharya et al., 2017; Engle, 2018). The approaches developed in this area are largely free from economic structure, in the sense that they rely on very loose, if any, assumptions on the functioning of markets, on bank behavior, or the macroeconomy as a whole. The CoVaR approach of Adrian and Brunnermeier (2016) for example, relies on quantifying the tail loss of the system, given that a single bank is in the tail of its equity returns distribution. While intuitively appealing, the quantile nature of their measure makes it difficult to decompose or add up to a total systemic figure. In contrast, the MES approach by Acharya et al. (2017) and the DIP measure by Huang et al. (2012) define codependency as the expected loss of a bank given that the system is its tail. The additivity of the expectation terms allows for a more intuitive aggregation of these measures, as we will show in Section 5. This is one of the reasons we follow their definitions of systemic dependence.[6] We thus relate to the few earlier

[5] Annex A.1 discusses the dataset used for the empirical evaluation.

[6] Note that the two approaches, the MES, and the DIP, are conceptually very similar. The main

approaches for quantification of systemic risk buffers as in Gauthier et al. (2012). Our approach, however is a top down exercise and we do not require transparency into the asset holdings of individual banks, but instead rely on market-implied dependencies.

There is extensive academic literature on macroprudential policy, but its focus is almost exclusively on interventions aimed at limiting household leverage in the mortgage market and on breaking the leverage-credit-housing build-up of systemic risk (Acharya et al., 2022). Instead, we look at regulators' ability to set additional buffer requirements on top of systemic banks' microprudential capital as a way of internalizing the implicit costs these institutions pose on the financial system. It should be noted that there is a link between our approach and the credit-leverage-housing prices cycle view on macroprudential policy: one can expect that funding of housing booms makes banks also more prone to joint distress. We aim to capture this feature by allowing for systematic factors to drive banks' asset portfolio correlations and consequently the probability of their joint distress.

Furthermore, we relate to the securitization literature on modeling the clustering of defaults in a credit portfolio (Vasicek, 1987; Hull and White, 2004; Gibson, 2004; Tarashev and Zhu, 2006). Conceptually, the universe of banks in an economy can be viewed as a portfolio of defaultable loans, where the liability size of each bank represents the exposure that stands at default, and the potential default losses are indicative of the relative cost each institution will impose on the economy if it becomes distressed. Systemic risk then relates to the potential for multiple large defaults to occur at the same time as in Huang et al. (2012); Puzanova and Düllmann (2013). The role of the regulator then is to manage the credit risk of that portfolio.

In terms of modeling of default probabilities, we relate to the literature studying bank fragility via structural firm modeling (Gropp et al., 2006; Chan-Lau and Sy, 2007; Bharath and Shumway, 2008). Most notable is the distance-to-default (DD) measure

difference is that the former defines the tail of the distribution of systemic scenarios as a quantile of the portfolio's distribution, while the latter sets it as losses above a fixed threshold. Informally, we will use a fixed threshold, but will still use the term MES as it has become more widely acknowledged in the literature.

(Merton, 1974; Crosbie and Bohn, 2002) which compares the current market value of assets to the default barrier of the firm. From that point of view, we contribute also to the literature on Distance-to-Capital, which relates Merton's DD to banks' regulatory capital requirements as in for example Harada et al. (2013); Chan-Lau and Sy (2007). We imply banks' asset variances from the observed CDS spreads and their observed CET1 capital holdings. This extends an idea developed by Russo et al. (2020) on linking the observed CDS spread to regulatory capital to imply banks' asset variance.[7]

At the same time, we relate also to the literature evaluating the long-term economic impact of capital buffers. One major strand of this literature solves for optimal capital buffers by equating the marginal social costs of raising buffers and making banks safer with the social costs this entails. The cost of having to raise more capital is often quantified through empirical estimates evaluating the overall effect of increased microprudential requirements on the economy, as in Miles et al. (2013); BCBS (2010); Firestone et al. (2017); Cline (2017). These approaches take it for granted that the Modigliani-Miller (MM) proposition on the neutrality of debt and equity financing does not hold, due to e.g. information asymmetries, bankruptcy costs, tax advantages of debt financing, etc. Usually, that makes capital a more expensive source of finance even if the market price of risk is taken into account.

Whether stricter requirements for equity financing (higher capital ratios) lead to higher risk-adjusted costs of financing for banks is an empirical question. Empirical arguments have been made in both directions. In fact, Admati et al. (2013) collect a number of strong arguments in support of (and evidence for) why deleveraging the financial system will present little if any higher risk-adjusted costs. In their view higher

[7]A recent critique on the use of the Merton model to evaluate banks' default risk needs to be acknowledged as well. Nagel and Purnanandam (2020) show that the Merton firm model misses a key property of the asset structure of banks: a bank does not share in the upside of the assets of the borrower. Banks' assets typically represent revolving collateralized loans whose payoff strongly deviates from the log-normality assumption embedded in the Merton model. As a result, estimating the Merton model in good times from observed equity value and variance may underestimate the true default probability of a bank. Our approach, however, implies default probabilities from observed CDS rates without reference to the Merton model, as shown in Annex A.4. In addition, the fact that we focus explicitly on downside tail risk scenarios, where the Merton model is relatively robust, mitigates concerns that systemic risk estimates may be underestimated due to the model's normality assumptions.

capital requirements would offset private incentives to take on socially excessive risk and thus would lower equity risk premia more than MM predicts, thus actually lowering the average cost of capital for banks; and second, would reduce the already distortionary incentives that come with e.g. any tax benefits or implicit government guarantees on banks' debt. Toader (2015) provides supporting empirical estimates for this view, arguing that the increased capitalization of European banks in the past has actually lowered their aggregate funding costs. More recently, Dick-Nielsen et al. (2022) use a large dataset of US banks and find that investors adjust their expectations in a way that preserves the MM proposition, basically rendering equity as expensive as debt once the price of risk is taken into account. On the other hand, Baker and Wurgler (2015) put forth the low-risk anomaly as a counterargument. They estimate that historical equity returns for less risky banks are higher on a risk-adjusted basis, a behavioral anomaly that is not strongly present in the debt market. As a result, MM's proposition on the irrelevance of the capital structure fails, and making banks safer may lead to higher aggregate funding costs for them, which may be passed on to the public in their view.

The strong disagreement in the literature is the reason why we prefer not to take a view on the size and social relevance of any MM offsets from equity financing. Instead, as we explain in Section 5.2.2, we rely on quantifying the short-term effects from higher macroprudential capital requirements on the size of the aggregate lending stock, an effect that has been documented more clearly empirically (Cappelletti et al., 2019; Degryse et al., 2020; Favara et al., 2021).

Alternatively, some have taken a more macroeconomic approach of equalizing at the margin the costs (in terms of reduced bank lending to the non-financial sector for example) and benefits in terms of lower expected costs of defaults. To do this credibly one would need to embed the framework in a full-fledged macro-finance model. Such models have been developed but they either tend to abstract from risk contagion between banks by modeling the financial sector as a single large bank, like in Cline (2017), or as a continuum of ex-ante homogeneous banks. Both approaches make the concept of ex-ante systemic importance difficult to implement in a practical application (Malherbe, 2020; Schroth, 2021; Mankart et al., 2020). We, therefore, offer two alternative approaches to quantifying the required macroprudential buffers: one which builds on actual practice and a novel approach more related to recent academic research on systemic risk and macroprudential policy.

In the first one, we stay close to the method followed by regulators in practice through what is called the EEI approach; EEI stands for Equal Expected Impact. Here, we relate to the policy-based literature on utilizing expected impact (FRB, 2015; Passmore and von Hafften, 2019; Jiron et al., 2021; Geiger et al., 2022).

In the second approach, we break from the current policy framework by developing a two-step optimization problem which can be used to determine the overall level of macroprudential capital and its allocation across systemic banks. First, we formulate the buffers problem as a constrained optimization problem of minimizing systemic risk subject to a target aggregate buffer level. Second, we take a macroeconomic approach and look at empirical estimates of the effect of lending shocks on short-term economic fluctuations (Barauskaitė et al., 2022) and combine them with estimates on the effect of increasing capital requirements on lending. This allows us, in the second step, to determine the socially optimal level of the average capital buffer. As a result, we avoid explicitly taking a stance on the MM controversy discussed earlier. Instead of aiming to quantify the impact on the cost of capital when capital buffers change, we directly look at estimates on the reduction of lending from banks subject to systemic buffer add-ons.

Both steps taken together allow for the derivation of a full set of bank-specific macroprudential buffers by also embedding in the estimates the trade-off between the expected costs of systemic defaults against the expected costs of reduced credit to the public, and thus potentially lower aggregate output, when buffers are raised.

2.2 Policy Framework

In the regulatory landscape, the G-SII framework addresses the capital buffers for banks which are systemic in a global context, while the O-SII framework in Europe captures the potential for spillover of financial shocks from domestic banks to the domestic real economy. In both cases central banks rely on a set of assigned regulatory scores of systemic impact to identify globally and domestically important banks. Broadly speaking, banks are ranked according to a number of indicators such as size, interconnectedness, substitutability and importance in the lending market, complexity, and cross-border activity. Based on each bank's overall weighted score, regulators determine the size of the add-on requirements on top of the minimum loss-absorbing capacity that banks have to hold. This is done either through approaches aiming to equalize the default-probability weighted scores between systemic and non-systemic institutions (the EEI approach), or through direct mapping from the systemic score of a bank to its capital requirement.

Both frameworks determine the size of an add-on capital buffer, where eventually banks need to satisfy only the larger of the two. The scoring approaches behind the two frameworks share a common background despite some nuances. In mapping from systemic scores to buffers, however, there are more notable differences. The G-SII framework relies explicitly on expected impact equalization, where the relative expected impact of a systemic bank gets equalized by higher capital buffers to that of a non-systemic bank (Cf. Section 4), while the O-SII framework allows either direct mapping (bucketing) or equalization approaches to be used. Cf. EBA (2020); ESRB (2017). ESRB (2017) recognizes that the majority of countries use a bucketing approach, in which banks with similar O-SII scores are bucketed together and assigned the same buffer requirement. However, the numbers of buckets and the methods for their classification differ across countries. For example, even though the favored method by most regulators tends to be an equalizing approach, the assumptions and parameter choice behind the methodology have been very diverse across countries in their implementation. This inevitably affects the calibration of the buffers, allowing national regulators discretion over the size of the buffer requirements on average.

3 A Model of the Banking System

In this section, we set up a model of the financial system with multiple banks subject to default risk. First, in Sections 3.1 - 3.4, we consider banks' default risk in isolation; and in Section 3.5 we define what drives distress correlations and look at how CDS data can be used to obtain the relevant empirical estimates. In Section 3.6 we introduce the measure of Systemic Cost of Default which takes into account the impact of a given bank's distress on the conditional probability of other banks to be in distress also. Finally, we analyse a quantitative example of the model in Section 3.7.

3.1 Financial Distress, Capital Requirements and the Default Threshold

There are N banks in the financial system; $i \in (1, \ldots N)$ is a bank indicator. Assume that a stochastic latent variable $U_i \sim N(0,1)$ governs the risks to a bank's creditworthiness over the coming one-year period. A higher realization of U_i indicates a better state of nature and consequently a lower default probability over the coming one-year period.[8]

Now assume that default occurs if the latent variable U_i falls below a threshold X_i. This leads to the following default indicator function:

$$\mathbb{1}_i \equiv \begin{cases} 1 & \text{if } U_i \leq X_i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

U_i is not directly observable by depositors or the regulator, not even when U_i crosses the critical threshold, more on which follows below.

[8]Bolder (2018); McNeil and Embrechts (2005) provide an extensive discussion of this class of default threshold models commonly utilized in the credit risk literature and in practice. Note that the model can easily be generalized to incorporate a non-Gaussian distributions for U_i, allowing for example for fat tails, skew and extreme dependency, which are often observed in asset returns. The securitization literature has developed a rich framework to account for that. In contrast to loan data, however, defaults in systemic institutions are rare, so any calibration of a richer parametric model than the normal distribution becomes difficult to justify. For this reason, we continue here with the standard Gaussian framework. However, it needs to be noted that even when the default of individual banks is governed by a Gaussian latent variable, the aggregated losses generated for the system will not be Gaussian.

Next, we relate the default threshold to the capital ratio of a bank. This will allow us to endogenize the threshold X_i and to measure the effect of capital regulation on banks' default probabilities. For the purpose, first we need to flesh out the basic fabric of the structural model which allows defaults.

Assume then that the (unobserved) market value of a bank's aggregate Risk Weighted Assets (RWA) $V_{i,t}$ follows Merton's dynamics (Merton (1974)) in continuous time under the risk-neutral distribution

$$d \ln V_{i,t} = r dt + \sigma_i dW_{i,t} \tag{2}$$

where r is the risk-free rate, σ_i is the standard deviation of the bank's RWAs, and $dW_{i,t}$ is a Brownian motion. Default occurs at maturity (time $t+T$) when the bank's RWAs fall below a fixed default threshold D_i.[9]

We can then write the default probability for the bank as

$$\begin{aligned} PD_{i,t} &= \mathbb{P}(V_{i,t+T} \leq D_i) \\ &= \mathbb{P}\left(V_{i,t} \exp\left((r - \frac{\sigma_i^2}{2})T + \sigma_i W_{i,t+T}\right) \leq D_i\right) \end{aligned} \tag{3}$$

Consider next the well-known measure of Distance to Default (DD):[10]

$$DD_{i,t} = \frac{\ln \frac{V_{i,t}}{D_i} + \left(r - \frac{\sigma_i^2}{2}\right) T}{\sigma_i \sqrt{T}} \tag{4}$$

[9]Our set-up is a minor adaptation from the original specification of the Merton firm model. We interprete $V_{i,t}$ as the market value of a bank's RWA, rather than of its total assets. This implies that σ_i should be interpreted as the standard deviation of the RWA. Also, in our setting, D_i needs to be interpreted as the default threshold in that relation as well. This allows us to interpret bank's equity-to-assets ratio directly in policy context, as capital requirements for the purposes the we consider here are set as a proportion of the RWAs (Cf. Annex A.2). Our specification can always be modified to match the original Merton set-up by adding a bank-specific scaling factor accounting for the ratio of risk-weighted to actual assets, as in Russo et al. (2020).

[10]Formally, DD measures the risk-adjusted distance at debt maturity from the expected firm asset-value to the default threshold: $DD_{i,t} = \frac{\mathbb{E} \log(V_{i,T}) - \log D_i}{\sigma_i \sqrt{T-t}}$. Cf. for example, Lando (2004) for clarifications and details on this.

Using this concept we can rewrite the expression for the probability of default as:

$$PD_{i,t} = \mathbb{P}\left(\underbrace{\frac{W_{i,t+T}}{\sqrt{T}}}_{U_i} \leq \underbrace{-DD_{i,t}}_{X_i}\right)$$

So we can interpret the term $\frac{W_{t+T}}{\sqrt{T}}$ as the latent creditworthiness variable U_i from Equation (1). Similarly, the default threshold X_i then equals the negative of Merton's DD.

Furthermore, denote as k_i the capital ratio of the bank: the fraction of its equity to its (risk-weighted) assets. Assume now that $T = 1$ and suppress the time t notation going further.[11] We abstract from debt maturity complications and assume that all bank debt is short-term. This seems reasonable since call deposits are the dominant liability of most banks. Equity is the asset value net of debt ($E_i = V_i - D_i$), so the capital capital ratio k_i equals:

$$k_i = \frac{E_i}{V_i} = \frac{V_i - D_i}{V_i} \implies \frac{V_i}{D_i} = \frac{1}{1 - k_i}$$

Inserting that expression into equation (4) implies the functional relationship

$$DD(k_i) = \frac{-\ln(1 - k_i) + \left(r - \frac{1}{2}\sigma_i^2\right)}{\sigma_i} \tag{5}$$

Finally, by combining (1) and (5) we get a relation between the default probability over a year from now and the current capitalization ratio:

$$PD(k_i) = \mathbb{P}(U_i \leq -DD(k_i)) = \Phi\left(\frac{\ln(1 - k_i) - \left(r - \frac{1}{2}\sigma_i^2\right)}{\sigma_i}\right) \tag{6}$$

Next, we discuss how to extract the σ parameter for each bank by observing banks' CDS spread and current capitalization.

[11] In assuming $T = 1$, we follow Lehar (2005) and interpret T as the time until the next audit of the bank, at which time an assessment takes place of whether the bank meets regulatory capital requirements.

3.2 Implying Banks' Asset Variances

Relationship (6) is useful in two ways. First, it provides the default probability which a regulator can then target by setting the overall capital requirements. This is the key mechanism through which the regulator in our setting will be able to reduce the contribution to systemic risk of an institution (cf. Sections 4 and 5).

In order to optimally set the capital requirements k_i with regard to the financial system as a whole, and not only with regard to the standalone risk of a single bank, the regulator needs to know the (co)variance structure of banks' asset returns. This is the second way in which equation (6) is helpful: it can be used to extract the implied asset variance from observable data.

To do so, we first extract the current default probabilities from observed CDS market prices by using the approach outlined in Duffie (1999) and Tarashev and Zhu (2006) which leads to the pricing formula:

$$PD_i = \frac{aCDS_i}{a(1 - ERR_i) + bCDS_i} \tag{7}$$

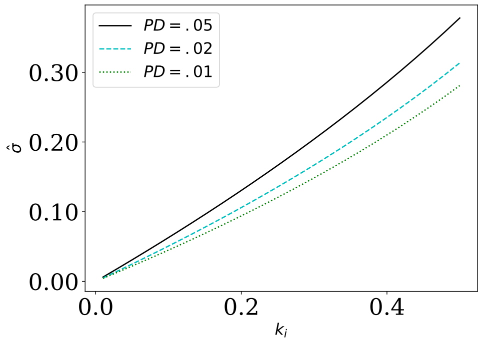
where a and b are known constants, CDS_i is the spread on the CDS contract written on bank i, and ERR is the expected recovery rate (RR) in case of default.[12][13]

Then, given the current capital ratio k_i and the CDS-implied default probability, we can derive the implied volatility of a bank's RWA's by inverting relationship (6) and solving it numerically for σ_i. We can thus write the implied volatility derived from (6)

[12] Annex A.4 provides the details behind this CDS pricing formula. We use an ERR assumption of 20% to extract the PDs, in line with the prospect of the subordinate CDS contracts provided in Bloomberg. Since we use subordinate debt CDSs on financial institutions, the standard ERR assumption is fairly conservative.

[13] The literature tends to employ a wide range of assumptions on the ERR term. In the systemic literature, it is particularly difficult to set the parameter as observations of defaults of systemic institutions and consequent valuation of the collateral are very rare. Puzanova and Düllmann (2013) set the ERR conservatively at 0%; Kaserer and Klein (2019) calibrate it based on the liability composition of the systemic institutions, assuming that deposits have a higher recovery rate than long-term corporate debt; Huang et al. (2009) set it to 55%; Huang et al. (2012) calibrate the ERRs to Markit survey data and show that they exhibit very little time variation.

Figure 1: Implied RWA Volatility



Note. This figure shows the relationship between bank capitalization and the asset variance implied through the Distance-to-Default relationship. We vary the level of the observed default probability and show how this shifts the implied curve.

as a function of the capital ratio and the PD_i we derived earlier:

$$\hat{\sigma}_i(k_{i,obs}, PD_i) \tag{8}$$

where $k_{i,obs}$ is the current observed CET1 ratio of the bank, and PD_i is the current default probability on which the bank's CDS trades.

Figure 1 illustrates the relationship between $\hat{\sigma}_i(k_i, PD_i)$ and k_i for three different levels of the default probability. Each upward-sloping line traces out $\hat{\sigma}_i(k_i)$ as a function of k_i for a specific value of PD_i. Increases in the observed default probability produce upward shifts in the curve. The figure shows, quite intuitively, that if we observe a highly capitalized bank whose debt protection is priced at the same level as that of a low capitalization bank, it follows that the market perceives the assets of the first bank to be riskier than that of the second bank. For a fixed PD, the higher the capitalization of a bank is, the higher the variance must be in order to produce the observed credit risk.

Table 2 in the Annex shows the implied asset standard deviations for the European sample of banks used in the consequent empirical analysis.

[13]We use a numerical root-finding algorithm to solve for the variance in (6) given a PD and $k_{i,obs}$. We utilize the Python implementation for root-finding of a scalar function with the '*brentq*' method, which applies Brent's root-finding algorithm.

3.3 On the use of Risk-Neutral Probabilities

Before we continue, it is worth discussing the set-up of the framework that we develop from a probability theory point of view. First, the model that we build is implied fully from asset prices and via option pricing theory. As a result, expected default losses and probabilities are based on the risk-neutral distribution (the **Q** measure), and cannot be interpreted as physical losses and probabilities, i.e. under the **P** measure. But we can nevertheless still calibrate the capital buffers by comparing the current expected value under **Q** of the distress losses of the banks in the system.

There are several reasons for that. First, in this setting macroprudential capital is determined through impact-equalization tools and distress minimization approaches. This is different from the standard risk management setting employed in micro-prudential regulation, in which capital buffers are set to cover the value of potential physical losses in e.g. 99.9% of the possible real-world scenarios.

Moreover, what matters for the size of the macro-prudential dependencies in our approach is implied asset variance and banks' distress dependencies, and we know from Girsanov's theorem (cf. Shreve (2000)) that only the drift parameter of a stochastic process is affected by the change of measure from **P** to **Q**, while its variance (or covariance matrix in case of a multidimensional process) is not.

Second, we know from asset pricing that that the *current* market consistent value of a financial contract is the same, regardless of whether (1) you evaluate the contract's future cash flows using expected values under the **P**-measure discounted by a corresponding risk-adjusted interest rate including the correct risk premium, or (2) whether one takes risk neutral expectations while using the safe rate of interest for discounting. The measures of systemic risk that we will define can then be interpreted as the fair value of a contract that pays off when a bank or the system is in distress. This is also the interpretation that for example Huang et al. (2012) use in defining their DIP (Distress Insurance Premium) measure of systemic risk, which is based on estimation of the risk-neutral probabilities of bank failure.

3.4 Micro and Macroprudential Capital requirements

Following the regulatory framework used by Central Banks, we assume that the capital requirements for each bank can be split into a micro- and a macroprudential component:

$$k_i = k_{i,micro} + k_{i,macro}$$

The micro component can be seen as the minimum regulatory requirement that banks need to satisfy in view of their own creditworthiness. These include to a large extent capital ratio requirements that are fixed at the same level for all banks, such as the minimum capital requirement (MCR) and the capital conservation buffer (CCB). We also allow, however, for a bank-specific micro component in order to capture Pillar 2 Requirements (P2R) (see Annex (A.2) for more detail).

The macro component, on the other hand, is a capital buffer set in the context of the system as a whole. Through this buffer, the regulator's objective is to safeguard financial stability. Going forward, we take the microprudential requirement $k_{i,micro}$ as a given, as its analysis is outside the scope of the regulatory task that we consider here.[14] Within this setting, the regulator only needs to determine the required minimum $k_{i,macro}$ as an add-on to the micro component for each systemic bank in order to curb the aggregate systemic risk.

We will represent k_i by Common Equity Tier 1 capital (CET1) with the view that it is the main going concern capital ratio in the Basel III framework. We abstract from the various types of capital and assume that CET1 is a good representation of a bank's equity.

Going forward, we take a two-step approach. In the first step, we derive the implied variance of the risk-weighted portfolio of assets for all banks from observing their current capital ratio and current default probability. In the second step, we abstract from the fact that banks may want to hold capital headroom above requirements, for example, to avoid ex-post penalties for violating the minimum capital requirements (cf Gornicka and

[14] For a discussion of the size of microprudential buffers, see BCBS (2010).

van Wijnbergen (2013)). Assuming that the minimum requirements are binding, we put all banks on an equal footing and vary the required macroprudential buffers above the minimum capital requirement and the capital conservation buffer.

3.5 Banks' Asset Correlations

In Section 3.1, we were modeling banks in isolation from each other. The next step is to set a process that drives the correlations between different banks' latent variables. In our approach, this is done through a set of common unobserved factors. The common component thus drives the probability of multiple banks becoming distressed at the same time. The exposure of each bank to these factors is determined by observing co-variations in the default probabilities of different banks. This approach is statistical in nature and we do not aim to find a direct interpretation of the factors; however, they have commonly been associated with market, industry, and geographically specific risk drivers (Pascual et al., 2006).

Formally, we can write:

$$U_i = \rho_i M + \sqrt{1 - \rho_i \rho_i'} Z_i \tag{9}$$

where $M = [m_1, \ldots m_f]'$ is the vector of f common latent factors, Z_i is the bank-specific factor, $\rho_i = [\rho_{i,1}, ..., \rho_{i,f}]$ is a vector of factor loadings, such that $\rho_i \rho_i' \leq 1$. Without loss of generality, all factors are selected to be mutually independent with zero mean and a standard deviation of one.[15] In our baseline model, we use the standard Gaussian Copula framework, where all factors M and Z_i are assumed to be generated by standard normal distributions. Furthermore, since we operate under the assumption of the Merton model, the covariance matrix is fixed and we do not presume the existence of correlation premia.

[15] The use of statistical/latent factors, estimated from the common time variation in asset prices appears often in the systemic risk literature, even with studies that do not track credit risk correlations. See for example Pelger (2020) who uses five-minute tick data from the NYSE to identify a statistical factor model accounting for systemic risk and finds economic interpretation for the factors; and Billio et al. (2012) who uses Principle Component factors to evaluate the evolution of systemic risk in the context of dynamic network interlinkages.

Note that one gets the well-known Vasicek loan portfolio model as a special case from Equation 9 by assuming a single common factor and the same factor exposure across all banks. Furthermore, note that the process in (9) is constructed to have a zero mean and unit variance, thus ensuring consistency on a univariate level with earlier assumptions (cf. Equation (2)).

In Annex A.3 we discuss the estimation procedure of the Gaussian factor model with a correlation matrix which itself is estimated from the default probability time series implied by the observed CDS spreads. Finally, Table 2 in Annex A.1 shows the fitted model exposures for the European sample of banks. This will be one of the key inputs in the our subsequent systemic risk analysis.

3.6 Systemic Costs of Default

Next, we construct a measure of the Systemic Cost of Default of a bank. The measure includes the expected losses in case of default of the bank, but also goes beyond that, taking into account how likely it is for the bank to become distressed at the same time as other related banks are distressed. We argue that a proper measure of systemic costs should capture four key properties:

- It should take into account distress dependencies between banks, thus focusing explicitly on the one-sided probability of the realization of joint tail events
- One should be able to decompose total expected costs into direct (due to the own default of a given bank) and indirect costs (due to the unexpected losses from the potential simultaneous default of other related banks)
- With zero correlation between a bank and all other banks in the financial system, its indirect effect should be zero
- The measure should be positively related to the relative size of the bank

To satisfy these properties we define the SCD for bank i as its (a) expected loss given that it is in distress (labeled *direct cost*), plus (b) the additional losses of all other banks conditional on bank i's distress, to the extent that their losses exceed their *unconditional* expected costs of distress. We label the latter term *indirect cost.* Both components are weighted by the bank i's own probability of distress.

We first define the potential losses for bank i one year from now as a fraction of its outstanding liabilities as

$$L_i = \mathbb{1}_i LGD_i \tag{10}$$

The losses are zero if the bank does not default ($\mathbb{1}_i = 0$) and are equal to the Loss Given Default (LGD_i) otherwise. Going forward, we will assume that the LGDs are known and fixed, in which case the only source of uncertainty is whether default happens or not.[16]

Next, define systemic losses L_{sys}, measured as a fraction of all outstanding liabilities in the system, as the sum of all banks' potential losses over the coming year L_i and weighted by the share w_i of their liabilities in the total liabilities of the sector:

$$L_{sys} = \sum_{i=1}^{N} w_i L_i \tag{11}$$

As a result, one can also view the size of the liabilities of individual banks in the sector as the Exposure at Default for the policymaker. This relates the model to the approach taken in the securitization literature to price portfolio of loans, where this model was initially developed.

This allows us to define the SCD for bank i as the expected default loss in the system, conditional on bank i becoming distressed, weighted by the probability of the bank

[16]Note that we write the following expression for the general case where LGDs are allowed to be heterogeneous across banks. In all applications however, we will assume that the LGDs are the same for all banks. In general, however, the same setting outlined here can be used even if they are modelled as random and possibly correlated processes across banks as in Dimitrov and van Wijnbergen (2023).

actually becoming distressed:[17]

$$SCD_i = \mathbb{E}(L_{sys}|\mathbb{1}_i = 1)PD_i \tag{12}$$

Due to the linearity of the expectations operator, we can break down the SCD into a direct component, corresponding to the weighted loss if bank i itself is in its tail, and an indirect component, corresponding to the expected loss of all other banks in the system again if bank i is its tail.

$$\begin{aligned}\mathbb{E}(L_{sys}|\mathbb{1}_i = 1) &= \sum_i w_i \mathbb{E}(L_i|\mathbb{1}_i = 1) \\ &= \sum_{j \neq i} w_j \mathbb{E}(L_j|1_i = 1) + w_i \mathbb{E}(L_i|\mathbb{1}_i = 1)\end{aligned}$$

Since the LGD terms are known and fixed for all i, we can then write the SCD as:

$$SCD_i = \sum_{j \neq i} w_j LGD_j \mathbb{E}(\mathbb{1}_j|\mathbb{1}_i = 1)\mathbb{P}(\mathbb{1}_i = 1) + w_i LGD_i \mathbb{E}(\mathbb{1}_i|\mathbb{1}_i = 1)\mathbb{P}(\mathbb{1}_i = 1)$$

Formally, define $PD_{j|i} \equiv \mathbb{E}(\mathbb{1}_j|\mathbb{1}_i = 1)$ as the default probability of bank i, conditional on bank j defaulting. Then, we can write the suggested systemic loss function as:

$$SCD_i = \underbrace{w_i LGD_i PD_i}_{\text{Direct Cost (Microprudential)}} + \underbrace{\sum_{j \neq i} w_j LGD_j \left(PD_{j|i} - PD_j\right) PD_i}_{\text{Indirect Cost (Macroprudential)}} \tag{13}$$

The expression above illustrates clearly how microprudential regulation directly targets the own default for bank i, while macro-prudential regulation acknowledges the fact

[17]Note that you can also write the term $\mathbb{E}(L_{sys}|\mathbb{1}_i = 1)$ as $\mathbb{E}(L_{sys}|L_i > \overline{L})$ where $\overline{L} < LGD_i$ is some loss threshold (more on it later). Then we can see this measure as a combination to the MES of Acharya et al. (2017) and the CoVaR by Adrian and Brunnermeier (2016). Similarly to MES, we evaluate average losses given that one entity is in the tail of its distribution. The difference is, however, that we invert the conditioning: we focus on a bank's contribution to systemic risk, not on its sensitivity to systemic losses. This allows us to relate to the regulatory framework which sets national and global systemic capital buffers to counteract the contribution each bank has on national or global systemic losses. From that point of view we also relate to the CoVaR.

that additional costs will occur because of unexpected defaults of other related banks, to the extent that the default of bank i correlates with defaults of these other banks. If bank defaults are uncorrelated we have that $PD_{j|i} = PD_j$, and the macro-prudential term disappears from Equation (13).

Also, Equation (13) shows that micro- and macro-prudential policies are not completely disconnected. There will be a positive spillover effect from one into the other: lowering the probability that bank i will default will not only reduce its direct systemic costs but will also lead to lower (expected) indirect costs associated with bank i's distress. At the same time, we can also see that the factors affecting the two types of policies are different: any change in the correlation between banks, for example, will affect only the macro and not the micro component, as it plays out only in the $PD_{j|i}$ terms and not in the PD_i.

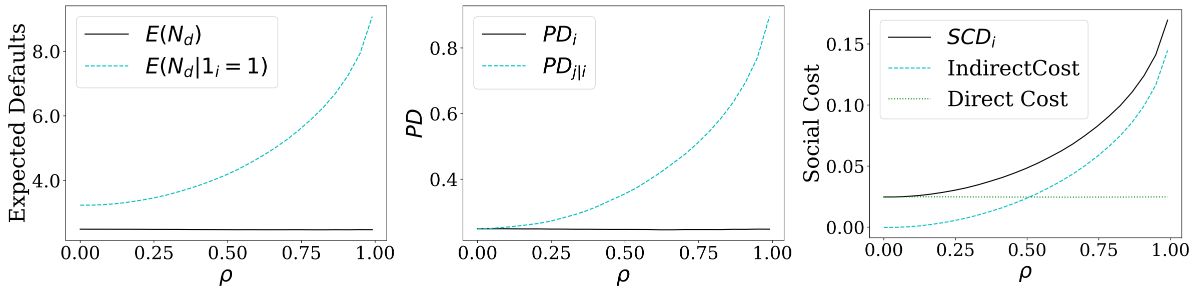
3.7 A Quantitative Example

Before turning to the empirical application in Sections 4 and 5 we will illustrate some implications of the model using a quantitative example. Assume for simplicity that there are ten equally-sized banks and that all their liabilities are lost in case of default, i.e. $w_i = 1/10$ and with $LGD_i = 100\%$. Assume further that in the base case all banks $i = 1, ..., N$ have the same high exposure to a single systematic factor such that $\rho_i = \rho$. Assume that banks stay at the minimum microprudential requirements of 7%.[18] Also, define $N_d = \sum_i \mathbb{1}_i$ as the total number of defaults in the system. We will vary consecutively the systematic factor exposure, the macro-buffer add-on for one of the banks, and the target bank's relative weight to the other banks, respectively.

In Figure 2, we vary the banks' exposure to the systematic factor ρ driving the correlation between banks' assets. The figure shows that as the correlation between banks increases, the expected number of defaults conditional on bank i's default ($\mathbb{E}(N_d|\mathbb{1}_i = 1)$) increases, while the average unconditional number of defaults ($\mathbb{E}(N_d)$) remains unchanged

[18] We use 7% micro buffers as a rough figure to capture the requirements of 4.5% CET1 capital and 2.5% CCB buffer and ignoring P2R at this point.

Figure 2: Asset Correlation



(a) Number of defaults (b) Default Probabilities (c) Social Cost Decomposition

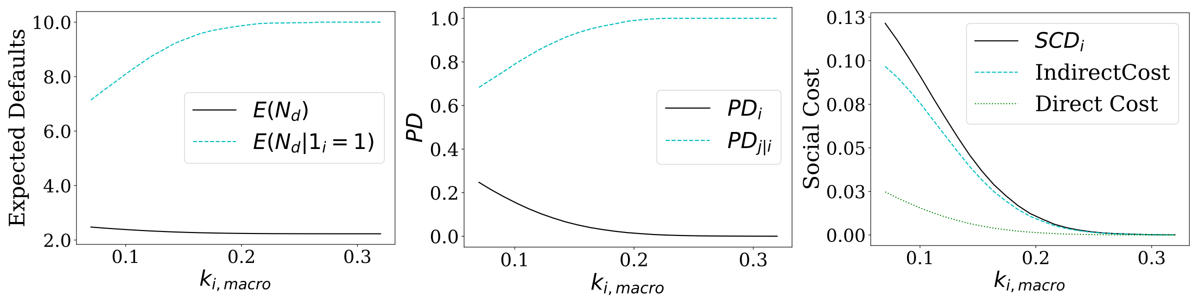
Note. This set of figures shows an example of a system with multiple banks. The charts illustrate the effect of higher bank asset correlations (through higher common factor exposures) on the number of defaults, on default probabilities, and thus on the estimated indirect costs, respectively.

(cf. Fig. 2a): the average number of (unconditional) defaults is unrelated to the degree of default correlation in the system. To get an intuition for this outcome, remember that statistically the expected value of several random variables, in our case representing the occurrence of default, is independent of the correlation between the variables. However, once we observe a single default, the likelihood of further simultaneous defaults occurring is higher when the system is more correlated.

A second and related fact is shown in Figure 2b: $PD_{j|i}$, the conditional default probability of another bank defaulting given a default in bank i, increases with ρ. The consequences of these dependencies for the SCD are shown in Figure 2c: the direct costs of default (the first term in the RHS of equation (13)) are independent of the correlation. But the indirect costs (the second term in the RHS of equation (13)) rise with increasing ρ, starting from zero when there there is no correlation between bank defaults. Obviously then, the total SCD (the sum of direct and indirect costs) equals the direct costs for zero ρ but increase with higher ρ in line with the indirect costs.

Consider next the effect of increasing the macroprudential capital requirement for bank i while keeping the capital requirement of all other banks at 7% (cf. Fig.3). We can observe several interesting facts. First, the unconditional expected number of defaults $E(N_d)$ decreases slightly since bank i's default probability is reduced. But conditional on bank i defaulting there is actually an increase in the expected number of defaults (cf. Fig.

Figure 3: Raising macroprudential Capital Requirements



(a) Number of Defaults (b) Default Probabilities (c) Social Cost Decomposition

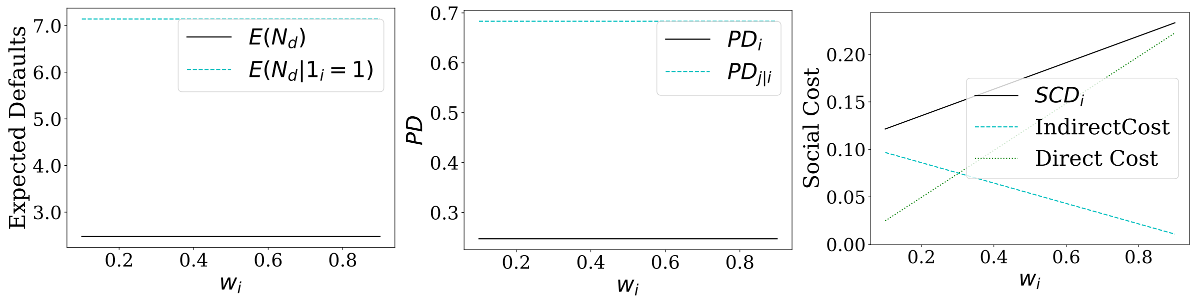
Note. This set of figures shows an example of a system with multiple banks. The charts illustrate the effect of higher macroprudential buffers on the number of defaults, on default probabilities, and thus on the estimated direct and indirect costs, respectively. The exposure of all banks to the systemic factor is set to $\rho = .9$.

3a). Similarly, the unconditional default probability of bank i goes down, when $k_{i,macro}$ goes up. At the same time, the conditional probability of another default happening given that bank i defaults actually increases in $k_{i,macro}$ (see Fig. 3b).

These results (a higher expected number of defaults and a correspondingly higher probability of default for bank $j \neq i$ *given that bank i defaults)* do not mean that the rest of the system becomes riskier. They captures the fact that as the default of bank i gets less likely, observation of it actually taking place indicates more severe market distress, which in turn implies that more banks will be affected on average. In our setting, severe market distress will materialize with the occurrence of a larger drop in the common factor M in the latent factor model (9). So increasing the capitalization of bank i does make the system safer, as can be seen in the gradual reduction in both the direct and indirect costs associated with the bank (Fig. 3c).

Finally, Figure 4 shows the effect of increasing the relative size of bank i while decreasing the relative size of all other banks proportionally so as to satisfy the adding up requirement $\sum_i w_i = 1$. The impact is not trivial: as w_i increases (and $\sum_{j \neq i} w_j$ decreases correspondingly), Figure 4c shows that the direct costs of default go up but that the indirect costs are in fact reduced. Other affected banks are still similarly affected but now they become relatively smaller. Bank i, on the other hand, becomes relatively larger

Figure 4: Relative Weight and the number of defaults, default probabilities and the SCD



(a) Number of Defaults (b) Default Probabilities (c) Social Cost Decomposition

Note. This set of figures shows an example of a system with multiple banks. The charts illustrate the effect of higher bank relative size on the estimated direct and indirect costs. As illustrated, the number of defaults and default probabilities are not affected by bank size.

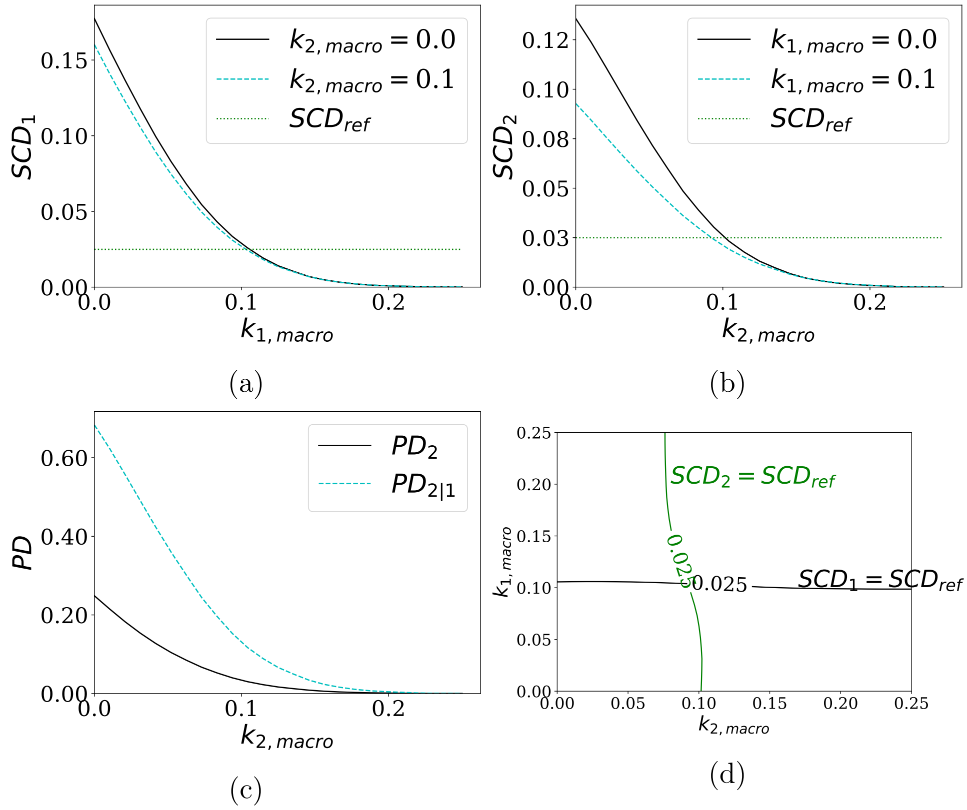
and has a larger direct impact on the system simply in terms of the total cost covering its own default. The net effect is that the SCD for bank i increases. To gain intuition into the direction of the net effect, relate this result back to the definition of SCD in equation (13): the fact that the term $(PD_{j|i} - PD_j)PD_i$ is positive (given that bank j is positively correlated to bank i) indicates that as w_i increases at the expense of the w_j-s, the relative sizes of all other banks, the bank's SCD will increase as well.

3.8 Positive Spillovers of Macroprudential Capital

When macroprudential requirements are set for a number of key institutions, the policymaker should consider potential positive safety spillovers between banks: increasing the macroprudential capital requirements of one bank lowers the SCD of other banks by reducing their indirect cost of default. This can be seen in equation (13): increasing the capital ratio of banks j, lowers the indirect costs for bank i as long as the $PD_{j|i}$ decreases faster than PD_j.

We illustrate the positive spillovers of capital regulation with another example. Building on our previous case, assume again that the financial system consists of ten players, each with the same exposure to the systematic factor of 0.9. Now, we assume that the first bank accounts for 50% of the total liabilities in the system, the second bank accounts for 20%, and that the other banks accounting for the rest are non-systemic and are equally sized. The policymaker sets macro capital buffers using the EEI approach. In doing so it needs to consider the interaction between bank 1 and bank 2's costs of default. That in turn implies that the regulator has to determine the optimal capital buffers simultaneously for the two systemic banks. Assume that the reference size of a nonsystemic institution is $w_{ref} = 10\%$.

Figure 5: Positive spillovers of a macroprudential capital increase



Note. This set of figures shows a quantitative example of a financial system consisting of multiple banks. Bank 1 and 2 dominate the sector with the former accounting for 50% of the sector and the latter accounting for 20%. Charts (a) and (b) illustrate the positive spillovers from making the other dominant bank safer; Chart (c) shows the effect of higher macro buffers on the bank's conditional and unconditional default probabilities. Chart (d) illustrates how the macro buffers of the two banks are set simultaneously in line with the EEI approach at the point where the two isolines cross and are equal to the SCD of the reference bank's SCD.

Figure 5 illustrates the impact of this interaction. First, consider Figure 5c where the PD of the second largest bank in the system (bank 2) is evaluated as its capital ratio is varied. As one should expect, both its conditional and its unconditional probability of failure are decreasing when more macroprudential capital is allocated to it (i.e. when

$k_{2,macro}$ goes up). Due to the positive correlation between the banks the $PD_{2|1}$ curve lies above the PD_2 curve: observing a default for bank 1 increases the chance we will also observe a default in bank 2 as well.

As $k_{2,macro}$ increases, both $PD_{2|1}$ and PD_2 converge to zero monotonously but $PD_{2|1}$ goes down faster than PD_2. As a result, looking at (13) from the point of view of bank 1, the difference term embedded in the indirect cost will be positive for any $k_{2,macro}$. This indicates that increasing the macroprudential buffer of bank 2 will both lower the direct SCD of bank 1 and its indirect costs. This is illustrated in Figure 5a: the $SCD_1(k_{1,macro})$ curve shifts down once $k_{2,macro}$ is increased.

A point worth noting is that as a smaller bank becomes safer, the positive spillover towards the larger bank will tend to be low in contrast to the spillovers towards a smaller bank when a larger one becomes better capitalized. In our example, as the smaller bank (bank 2) has its macro capital buffers increased from 0% to 10%, this hardly shifts the SCD curve for the large bank (bank 1) to the right; see again Fig. 5a. But when the much larger bank 1 becomes better capitalized, the reduction in the SCD for bank 2 is much more substantial (see Fig. 5b).

In the next section, we discuss the Equal Impact approach to macroprudential capital buffers, which is widely used in practice. In this approach the regulator picks the macroprudential requirements aiming to set the SCD of each systemic bank equal to the SCD of a reference non-systemic institution (SCD_{ref}). In Figures Figures 5a and 5b this is represented by the straight dotted line. Note in that case that the effect of the positive spillovers is lower, the lower the reference SCD is. The reason is that a low reference SCD implies a more conservative policy, in the sense of a stricter requirement for banks to increase their own capital. With high levels of own capital, the PD of a bank is already close to zero, implying that capitalizing other banks in the system cannot lower SCD for this particular bank much further. Thus, in Figure 5b shifts to the right of the SCD_2 curve (with increased macro buffers of bank 1 from 0% to 10%) become negligible when bank 2 itself is already well capitalized, in this example with $k_{2,macro}$ above 10%.

As we just argued, the two systemic banks in our example influence each other. This means maintaining one bank's SCD at the desired SCD_{ref} level can be done by either using its own macro buffer or by adjusting the buffer of the other systemic bank. This is demonstrated in Figure 5d where we show the two iso-SCD contours for respectively bank 1 and bank 2. The two banks will both have a SCD equal to the reference SCD_{ref} at the point where the two iso-lines for $(k_{1,micro}, k_{2,micro})$ cross. The non-linearity we are discussing is exemplified by the fact that the iso-SCD curves are not strictly vertical (for bank 2) or strictly horizontal (for bank 1). Since the shifts in SCD from the safety spillovers become larger when the reference SCD is larger, the non-linearity will become correspondingly more prominent in that case.

Up until now, we have explored the concept of systemic risk arising through asset correlations and among other things discussed the sometimes surprising impact of capital buffers on the SCD of both a given institution and of the system as a whole. Evaluating the SCD of banks can be a useful way to measure the systemic importance of banks. That analysis in itself, however, does not tell us (or regulators) how high these buffers should be in order to safeguard financial stability. The obvious next step is to ask precisely that question. We show two approaches in answering this question. First, the Expected Equal Impact approach we already touched upon briefly, and second, a more general explicit optimization-based approach using Acharya et al. (2017)'s Expected Shortfall concept.

3.9 A Note on our Banking Model

Before proceeding with the model calibration, we need to discuss one key embedded assumption of the model. Implicit in our setting is the assumption that once a policymaker changes the capital requirements, banks will comply directly. Modeling any potential shifts in the risk choice of banks, and endogenizing asset correlations or variances is outside of our scope. There are several reasons for that. First, the loans that banks hold at a given moment of time are typically fixed over the medium run, so shifts in the composition of the portfolio are not immediately feasible. Risk choice thus concerns only new loans, and it will take a while before a bank is able to achieve a new desirable risk allocation. Second, in light of the lack of strong empirical evidence of how banks react to increased capital requirements, endogenizing risk choice would expose our results to the possibility of stronger model misspecification. Dependent on the type of friction that the bank is experiencing, debt overhang with respect to the old loans or risk shifting with respect to new loans, the optimal reaction of a bank to capital requirement may go either way (Bahaj et al., 2016; Bahaj and Malherbe, 2020; Jakucionyte and van Wijnbergen, 2018). As a result, we focus on the more tangible interactions that can be estimated with reasonable accuracy from the available data and assuming that variance and factor exposures remain static as indicated in (6) and in (9). Another way to see our assumption of fixed asset variance is as the the skin in the game effect, which curbs risk taking Holmstrom and Tirole (1997) being offset by the effect of reduced franchise value Hellmann et al. (2000) which incentivizes risk-taking by reducing the private cost of default.

Finally, we need to address several concerns typically raised regarding the use of CDS prices in estimating banks' default probability and default correlations. First, we focus on CDS prices of contracts written on subordinate debt. Subordinate debt is typically not rescued during bail outs, so the corresponding CDS contracts are not contaminated by the implicit put option provided by Central Banks' bail outs. Furthermore, for centrally cleared contracts counterparty risk is largely eliminated, thus removing another potential source of pricing noise. There are possible liquidity issues, but illiquidity is often a precursor of insolvency, so we do not try to explicitly incorporate liquidity risk premia. Diamond and Rajan (2011) for example make the argument that illiquidity and insolvency are difficult to disentangle: illiquidity is often an indicator of higher credit risk. Brunnermeier and Pedersen (2009) also argue that funding liquidity and market liquidity are strongly interconnected. In that sense, funding liquidity is linked to default probably, while also less liquid CDS contracts could indicate that the market is not willing to fund contracts dependent on a firm's credit prospects.

Overall, relying on market data offers an objective way to verify the adequacy of the currently assigned macroprudential buffers and eliminates the well-documented drawbacks of using transactions data, balance sheet data and regulatory scores to assess systemic importance.[19]

4 The EEI Approach with Default Correlations

4.1 Systemic Risk and the EEI framework: Theory

The philosophy behind the EEI approach is to use the additional macroprudential buffers as a way to bring down the expected social cost of default for a systemically important institution to that of a reference non-systemic anchor. The cost of default, in the G-SII and O-SII regulatory frameworks, is measured through the scores assigned to institutions according to their size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity. The overall score, thus, provides rough guidance on the institutions' systemic importance. In this case, a low threshold value can be used as an anchor representing a non-systemic reference institution. Eventually, the probability-weighted score of each systemic institution needs to be equalized to the corresponding probability-weighted score of the anchor.

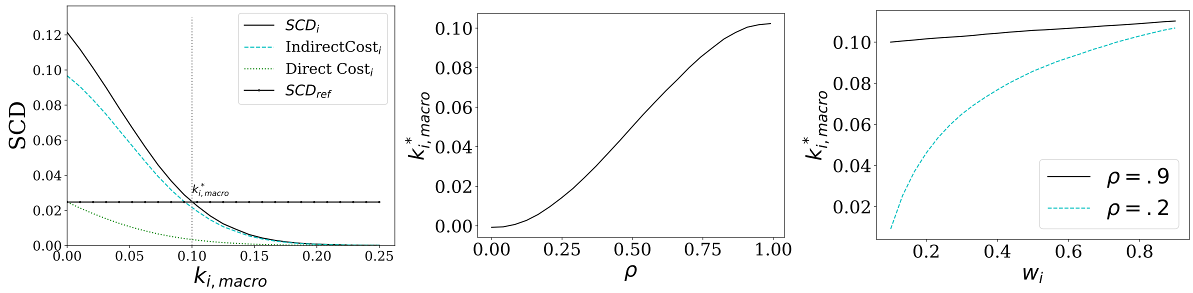
But when systemic risk as a consequence of asset return correlations is explicitly recognized, an alternative way of implementing the EEI approach becomes apparent, one where the expected tail-risk impact of distress is equalized by taking explicitly into account the empirically measured default correlations between institutions. We discuss this alternative now.

Consider the fact that default probabilities are a function of capital requirements through the default threshold approach established in (4). We can then define the SCD of a benchmark or reference institution which has no indirect cost associated with other institutions, and as a result, holds only micro-prudential capital:

$$SCD_{ref}(k_{i,micro}, w_{ref}) \equiv w_{ref} LGD_{ref} PD(k_{ref,micro}) \tag{14}$$

[19] For example, a number of studies find that G-SIBs tend to reduce activities affecting their systemic scores at year end ahead of the reporting date, presumably as a way to lower their capital buffer surcharges (Behn et al., 2019; Berry et al., 2021; Garcia et al., 2021).

Figure 6: Optimal Macro Buffers



(a) (b) (c)

Note. Figure (a) shows the optimal macroprudential buffers for a bank using the EEI approach. Charts (b) and (c) respectively show the optimal buffer if we vary the common factor exposure, and thus the average default correlation between the banks in the system. Chart (c) shows the results if we vary the relative size of the bank.

Refer to this bank as the *reference bank*. The next step is to equalize the SCD of bank i presumed to have a systemic relevance to the expected SCD of the reference bank. This is done by requiring the systemic bank to raise its capital ratio by $k_{i,macro}$. In that sense, the macroprudential capital requirements are *additional* buffers that come on top of the stand-alone microprudential buffers $k_{i,micro}$:

$$SCD(k_{i,micro} + k_{i,macro}, w_i; \rho_i) = SCD_{ref}(k_{ref,micro}, w_{ref}) \tag{15}$$

Figure 6a visualizes the impact of macroprudential buffers by plotting the SCD against macroprudential capital requirements $k_{i,macro}$ using the parametrization from the base example discussed earlier in Section 3.7. We, first of all, show the SCD associated with the reference institution in this figure; for that institution, $k_{i,macro} = 0$. This benchmark line is labeled SCD_{ref}. Obviously, this is a horizontal straight line, since the macroprudential buffer that is varied along the horizontal axis does not apply to the reference institution.

The SCD line for the systemic bank starts at $k_{i,macro} = 0$, and, as the diagram shows, is much higher at that point than the SCD of the reference institution, which of course is why the systemic bank is subjected to macroprudential buffers, to begin with. Both banks' microprudential buffer is set at 0.07 in this example. Figure 6a furthermore indicates, in line with previous discussions, that the social costs (both direct and indirect) of the systemic bank's distress are decreasing when higher macroprudential capital requirements are applied: cf the downward sloping line labeled SCD_i in Figure 6a.

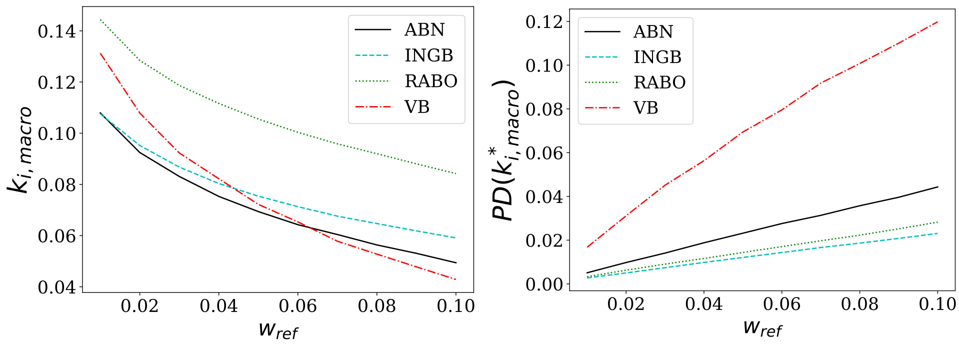
The regulator can derive the buffer that will establish equal expected impact by raising $k_{i,macro}$ and so lowering the systemic bank's SCD to the point where it equals SCD_{ref}. At that point, the default probability of the systemic bank is lower than the default probability of the reference bank to such an extent that its total expected SCD is equal to the SCD of the reference bank. This happens at the point where the SCD_i curve crosses the SCD_{ref} line at $k_{i,macro} = k^*_{i,macro}$ in Figure 6a, where the macro add-on is calculated to be slightly below 10%.

Figure 6b shows the optimal macroprudential buffer ratio $k^*_{i,macro}$ as a function of the bank's exposure to the systematic factor, captured by ρ. Higher exposure to the factor implies a higher correlation between bank pairs, which in turn results in a higher indirect cost component of the SCD for the bank. And therefore a higher ρ leads to a higher optimal macroprudential capital requirement $k_{i,macro}$: the $k_{i,macro}(\rho)$ line slopes upward in Figure 6b.

Figure 6c shows, for two different values of the correlation parameter ρ, the impact on $k^*_{i,macro}$ of increasing the relative size of bank i at the expense of the other non-reference banks in the system. The reference bank weight in the EEI calculation is kept fixed at 10%. For the high correlation case ($\rho = 0.9$) relative size obviously does not matter too much. The reason is that in that case what happens with one bank is more than likely to happen with the others too at the same time, so even when the bank is smaller, it is optimal for the regulator to require that it holds high macro buffers. The curve then is relatively flat when w_i starts increasing. But for low correlation (in the figure the line corresponding to $\rho = 0.2$) relative size does have a significant impact on the optimal macroprudential buffer size. For low ρ we find that the larger bank i is relative to the rest, the more aggressive the macroprudential requirements should be. The larger the bank is, the more it dominates the system, so even with low correlation, the optimal $k_{i,macro}$ converges to the high correlation case as the relative size of the bank under consideration increases.

4.2 Systemic Risk and the EEI framework: Empirics

Figure 7: Optimal Macro Buffers: EEI Approach



(a) Macroprudential Capital

(b) Default Probability

Note. This figure shows (a) the implied macroprudential buffers for the Netherlands; and (b) the corresponding probability of default as a function of the size of the reference bank. Table 3 in Annex A.5 shows the complete model results for all countries in the analysis.

With the theory behind the EEI approach worked out, we next present an empirical application of the model. Figure 7 presents the results for the Dutch subsample of banks in order to illustrate the main point on the analysis. Part (a) shows the resulting macroprudential capital from by equalizing each bank's impact to that of the reference entity. Part (b) then shows the resulting default probabilities at that level of capital.

The reference entity is constructed by assuming that it has zero exposure to the systemic factors, holds only microprudential capital, and the volatility of its assets is equal to the average of the asset volatility for all banks in that country.

In the figure, we show the impact of varying the size of the reference institution w_{ref} on the buffers estimated through the EEI approach. As we saw earlier, the smaller the assumed reference size, more conservative is the policymaker in setting the optimal macro buffers and the lower the tolerance is for individual bank default. In other words, the lower the threshold for designating a bank as systemic, the higher the capital buffers will be for all systemic banks which are managed by that anchor, and thus the lower the tolerance for their default will be. As a result, capital buffers are decreasing, while the default probabilities of individual banks are increasing with the chosen size of the reference institution.

For a smaller bank, such as for example VB in the Netherlands, the default probability is allowed to be higher over the range of reference scenarios, while the default probability of a larger bank as INGB in the same country is suppressed significantly. The size of the assigned capital buffers, however, does not correlated perfectly with size. The largest buffers are assigned to RABO, which is the second largest bank in the Netherlands after ING. This is the result of the bank being the more sensitive to systemic factor shocks with exposure to the main common factor ρ_1 of .95 versus .75 for ING. Furthermore, RABO's implied asset standard deviation is higher than that of the other two large banks, INGB and ABN, as can be seen in Table 2.

For completeness, we apply the same approach to each country in our sample. Again, the system in each case is considered to be the set of banks domiciled in that country, thus mimicking the current regulatory process behind the O-SII framework. The same findings illustrated above are confirmed here as well.

Overall, we find that the EEI buffers are larger than the range within which current O-SII buffers have been set (within the range of 0% to 3% for the sample period). One potential reason for that difference is the fact that unlike the regulatory expected impact approaches, the SCD that we use explicitly incorporates the sensitivity of other banks' default to the default of systemic bank, the indirect component. The regulatory approach captures interconnectivity only fractionally through the regulatory systemic score based on intrasystem holdings (EBA, 2020; BCBS, 2021).

5 The Expected Systemic Shortfall Approach

One potential downside of the EEI approach is its dependence on an arbitrarily chosen and sized anchor. Regulators may not have a reliable way to pick the key parameter of the equalization method: the relative size of the reference institution (w_{ref}). Or similarly, they may be unable to defend their parameter choice as it inevitably leads to the question of how large a bank can be before it is considered systemic. Instead, a regulator may have a much better view on what is the average capitalization that the sector can handle without hurting the lending capacity of systemic banks excessively, thus slowing down economic activity.

We therefore develop an alternative approach to calibrate the buffers, again relying on the credit framework of Section 3. Going forward, in Section 5.1 we first work out the theory of what we label the ESS approach, and in Section 5.2 we apply it empirically. In the process, we estimate the capital buffers in two steps. First we apply the minimum risk approach to the calibration of systemic buffers, targeting the current average level of O-SII buffer rates set by the regulator. After that we investigate whether the average O-SII rate corresponds to a socially optimal solution which balances the costs and benefits of an increase in capital buffers.

5.1 The Expected Systemic Shortfall Approach: Theory

The ESS approach starts out with a policymaker who takes a portfolio risk-management perspective to the banking sector as a whole; but rather than targeting a fixed anchor like in the EEI approach, the regulator aims to minimize the downside risk of the whole portfolio. The risk of the portfolio is managed by assigning macroprudential buffers across banks deemed to be systemic, thus lowering their impact on the potential portfolio losses. The policymaker controls the overall level of accepted risk by setting a target average buffer rate and then allocates bank specific buffers around that average. This set-up is in fact inspired by Acharya et al. (2017) who allocate bank specific macroprudential tax rates subject to an average target. We directly target the systemic banks' capitalization.

5.1.1 Expected Shortfall and Systemic Risk

The banks in our policymaker's portfolio constitute the financial system. We then define the Marginal Expected Shortfall (MES) of a bank as its average loss conditional on total systemic losses being above a threshold $\overline{L}$:

$$MES_i = \mathbb{E}\left(L_i | L_{sys} > \overline{L}\right) \tag{16}$$

The parameter $\overline{L}$ can be seen as governing the policymaker's tolerance to systemic losses, as it indicates the aggregate losses as a percentage of the outstanding liabilities above which regulators assume that a systemic financial crisis is occurring. A higher level of $\overline{L}$ indicates that the policymaker is willing to tolerate larger losses before stepping in. Therefore the higher the intervention threshold $\overline{L}$ is, the lower the level of the macro buffers.[20]

We can also quantify aggregate systemic risk (Expected Systemic Shortfall, ESS) as the potential default loss on a portfolio containing all banks in the financial system for which the supervisor is accountable given that that aggregate loss exceeds $\overline{L}$:

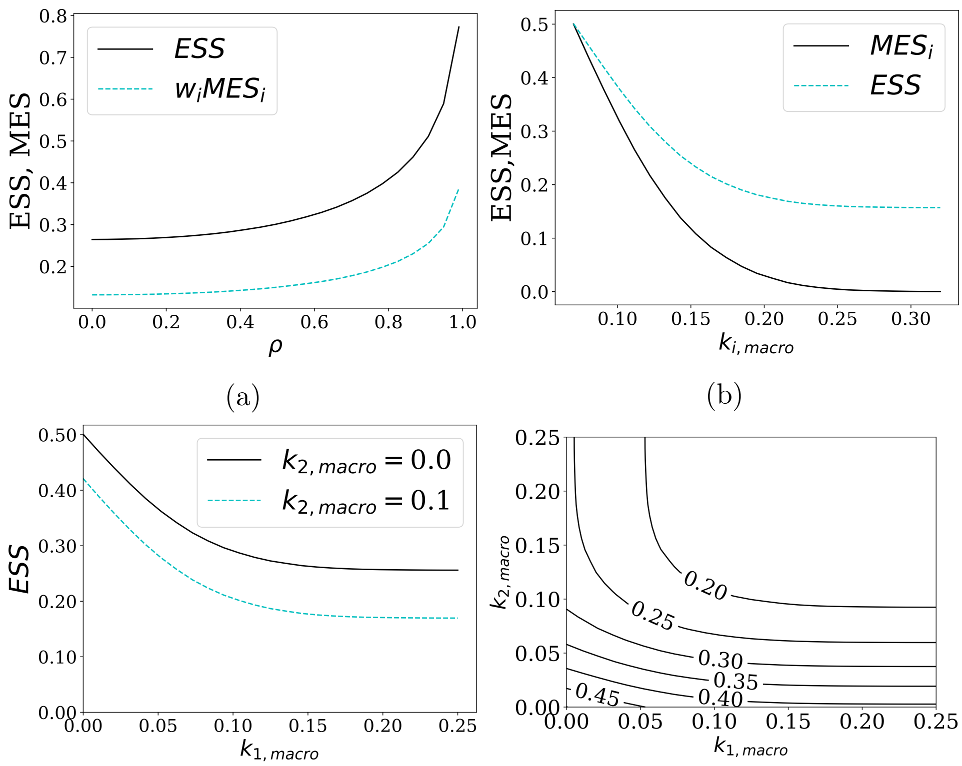
$$ESS \equiv \mathbb{E}\left(L_{sys}|L_{sys} > \overline{L}\right) = \sum_i w_i MES_i \tag{17}$$

where the last line follows from the additivity property of expectations and the fact that all MES_i terms are conditioned on $L_{sys} > \overline{L}$. This provides a useful interpretation of the MES: a bank's weighted MES represents the portion of total systemic risk that it brings in. Lowering the bank's MES by imposing higher capital buffers thus will lower overall systemic risk.

Figure 8 illustrates the behavior of the MES and the ESS using the example set-up considered earlier. Our findings about the properties of the SCD in Section 3.6 also apply here. First, the ESS and the weighted MES increase with the correlation between banks' assets (cf. Fig. 8a). Second, higher capitalization of bank i lowers its MES and thus lowers total systemic risk (cf. Fig. 8b). Third, the positive spillovers from increased capitalization of one bank also apply here: the optimal macroprudential buffer for bank 1 becomes lower, once the buffer for bank 2 is raised (cf. Fig. 8c). Finally, Figure 8d shows the combination of bank 1 and bank 2 buffers which can produce the same level of systemic risk.

[20]We calibrate the parameter $\overline{L}$ in Section 5.1.3. Note also that we use the MES naming loosely here, as strictly speaking the original Acharya et al. (2017) measure defines $\overline{L}$ as the tail quantile of the distribution, while we define it as a fixed threshold in line with the Distressed Insurance Premium (DIP) measure of Huang et al. (2012).

Figure 8: Expected Systemic Shortfall



(a) (b) (c) (d) ESS

Note. This figure illustrates quantitatively the properties of the ESS and MES in a universe with 10 banks. The same set-up as in Section 3.8 is used.

Writing the ES of the system as a function of all banks' capital ratios we can reformulate the policymaker's problem as one of minimizing total ESS by choosing the size of the macro buffers for each bank in the system simultaneously:

$$
\begin{aligned}
ESS(\overline{k}) &= \min \sum_{i=1}^{N} w_i MES(k_{i,macro}) \\
s.t. \quad & \sum_{i=1}^{N} w_i k_{i,macro} = \overline{k}
\end{aligned}
\tag{18}
$$

where $\overline{k}$ is a target average macroprudential add-on, and $MES(k_{i,macro})$ evaluates (16) for bank i given a macro buffer of $k_{i,macro}$ on top of the microprudential requirement.[21]

[21] Equivalently, this optimization can also be seen as maximizing the net benefit of reduced systemic

5.1.2 Determining the optimal $\overline{k}$

The obvious next question is: what should the optimal level of *average* macroprudential buffers $\overline{k}$ be? Policymakers, as indicated earlier, will use this quantity as a target against which to allocate systemic buffers between banks.

For this purpose, we look at the policymaker's problem as one of maintaining a healthy supply of credit in the economy while managing the risk of a systemic crisis from materializing. Higher capital requirements reduce the probability of a financial crisis, but they also bring the risk of inducing a reduction in lending if banks struggle to satisfy the stricter regulatory constraints. The policymaker thus needs to balance the two costs for the economy. We formalise this choice by for a start defining a welfare cost function measuring the social cost of holding capital buffers:

$$W_c = \underbrace{\lambda \cdot ESS(\overline{k})}_{\text{GDP Loss in a Banking Crisis}} \cdot P(\overline{k}) + \underbrace{\eta(\overline{k} - \overline{k}_0)}_{\text{GDP Loss in Raising Buffers}} \cdot (1 - P(\overline{k})), \quad \overline{k}_0 = 0 \tag{19}$$

In this setting, $\overline{k}_0$ is the initial level of macroprudential capital buffers, λ is a multiplier, to be define next, which translates expected tail losses in the financial sector to losses for the wider economy, expressed as a decline in GDP. We define the probability of a financial crisis $P(\overline{k})$ and the expected losses in a financial crisis $ESS(\overline{k})$ endogenously, where the macro-prudential buffers accross banks are determined optimally in line (18).

It is straightforward to show that:

$$\frac{\partial P(\overline{k})}{\partial \overline{k}} < 0; \frac{\partial ESS(\overline{k})}{\partial \overline{k}} < 0$$

risk compared to the case with micro-buffers only. In that case, the objective can be written as

$$\max \left\{ \sum_i w_i \left(MES(0) - MES(k_{i,macro}) \right) \right\}$$
$$s.t. \quad \sum_{i=1}^{N} w_i k_{i,macro} = \overline{k}$$

producing essentially the same optimization problem.

where the partial derivative reflects what we already established earlier, that higher overall buffer levels lower the probability of individual and systemic distress and the realized systemic losses.

Note that $\overline{L}$ determines the intervention threshold for the regulator, and implicitly can be linked to the regulator's loss tolerance. Below $\overline{L}$ the regulator provides LoLR funding to stave off a crisis, but when losses exceed $\overline{L}$ a financial crisis becomes unavoidable. In line with the previous section, we treat all losses on a relative scale, i.e. as a percent of the size of the system measured by the outstanding liabilities of the financial sector.

On the other hand, if no systemic distress occurs, the public has to bear the cost to the economy of imposing $\overline{k}$ capital buffers. We quantify this cost through the response of aggregate output (Y) to an increase in capital requirement. This response runs via reduced credit lending in the economy, as banks need to satisfy the higher capital requirements by accessing the possibly more expensive source of financing that common equity imposes, or by reduced risk-shifting incentives.[22] Our goal is to quantify this response as the relative rate of change term, but without specifying a full-blown macro model:

$$\eta = -\frac{dY/d\overline{k}}{Y} = -\left(\frac{dY}{dC}\frac{C}{Y}\right)\left(\frac{dC}{d\overline{k}}\frac{1}{C}\right) \tag{20}$$

where C is the total equilibrium level of credit in the economy. η then represents the percentage drop in GDP for a one percentage point increase in the macroprudential ratio requirement.

Finally, the policymaker chooses the optimal $\overline{k}$ that minimizes (19). The first-order condition implies that at the optimum $\overline{k}$ the expected benefits of a marginal increase in the macroprudential capital levels in terms of reduced expected crisis losses just compensates for the marginal increase in the macroeconomic costs associated with an increase in the

[22] Cf. Jakucionyte and van Wijnbergen (2018) for a discussion on the macro effects of higher capitalization of the banking system with risk-shifting and debt overhang problems through the latter's impact on aggregate credit supply.

aggregate level of the macroprudential buffers in the absence of a financial crisis:

$$\lambda\left(P\frac{\partial ESS}{\partial \overline{k}} + \frac{\partial P}{\partial \overline{k}}ESS\right) = \eta\left((\overline{k} - \overline{k}_0)\frac{\partial P}{\partial \overline{k}} - (1 - P)\right)$$

5.1.3 Calibration of the welfare cost optimization

Consider now the parametrizing of the optimization problem (19) which will allow us to set the socially optimal average buffersize $\overline{k}$. The core assumption behind our approach is that increased capitalization requirements will lead to a negative lending shock; low average capitalization, on the other hand, will lead to increased probability of a financial crisis and increased welfare loss. We refrain from making explicit assumptions about the channel through which lending is reduced, this would require a full banking model, which is outside of the scope of this paper. Also, we refrain from the approach used in part of the literature of quantifying specific Modigliani-Miller deviations and of estimating the subsequent pass-through of the associated higher financing costs to the public.[23] Empirically, the two questions have been a matter of debate: see for example Dick-Nielsen et al. (2022), who cast doubt on the claim that deviations from MM would increase significantly the cost of capital to banks.

Instead, we focus on studies quantifying the relationships between output and lending shocks on one hand, and lending decline due to capital requirements on the other. By combining the two, we hope to capture the overall causal effect from increased capital requirements to output losses.

Empirically, macroprudential buffers have been found to constrain the supply of credit for the individual banks that are targeted. Using regulatory data Cappelletti et al. (2019) find that in the short run banks identified as O-SII cut the credit supply to households and the financial sector, even though in the medium run this tendency is diffused. In a diff-in-diff setting Behn and Schramm (2021) do not find a significant effect on the overall lending activity of G-SIB designated companies, but find a significant shift towards

[23] Cf. Cline (2017); Brooke et al. (2015); Miles et al. (2013) for an extensive discussion of the approach using MM offsets.

lending to less risky counterparties. Degryse et al. (2020) find a more pronounced effect by focusing on a narrower time window and unexpected G-SIB designations. Favara et al. (2021) look at the US and find that banks designated as G-SIBs do reduce their credit supply but the aggregate effect is muted as firms switch to non-G-SIB banks. In their estimate, a one percentage point increase in macroprudential capital surcharges leads to loan commitments by GSIBs banks to fall by 3–4% on average relative to other banks. We use their upper estimate as the most conservative figure on the negative impact of capital requirements on the supply of credit on the economy in the short run. This gives us an estimate of the term $(dC/d\overline{k})(1/C)$ in 20.

On quantifying the impact of reduced credit supply to lower GDP growth, we rely on Barauskaitė et al. (2022), who in a BVAR framework identified with sign and inequality restrictions, determine that a 1% reduction in loan supply would result in a worst-case scenario in about .6% reduction in GDP growth.[24] This provides an estimate of $(dY/dC)(C/Y)$. Combining these two numbers (4% and 0.6%) gets us a baseline figure for the η in equation (20) of .024.

Table 1: Model Calibration

Variable	Value	Source
$\overline{L}$	.09	Implied from Laeven and Valencia (2020)
$(dY/dC)(C/Y)$	.006	Barauskaitė et al. (2022)
$(dC/d\overline{k})(1/C)$	-.04	Favara et al. (2021)
η	.024	$(dC/d\overline{k})(1/C)(dY/dC)(C/Y)$
λ_{sev}	.22	Implied from Reinhart and Rogoff (2009)
λ_{mod}	.15	Implied from Romer and Romer (2017)
λ_{mild}	.98	Implied from Romer and Romer (2017)

Note. This table shows the parameter values for the policymaker social optimization problem. All parameters are in decimal points.

Next we need to calibrate $\overline{L}$, the threshold loss parameter of government involvement to prevent a financial crisis from becoming systemic. To do that, we refer to Laeven and Valencia (2020) who evaluate bank restructuring fiscal costs associated with systemic crises to at least 3% of GDP. This number has also been used as a minimum bank capital

[24]Refer in particular to Figure 3 in Barauskaitė et al. (2022) outlining the impulse-response functions from a credit supply shock.

shortfall rate in policy exercises, as in Brooke et al. (2015). Within the Euro-area for the period under consideration, total bank liabilities are around three times the value of GDP, which implies an $\overline{L}$ of around 9%.[25] Note the current conservative assumption of LGD of 80% implies that expected number of defaults at threshold will be $\sum_i w_i \mathbb{1}_i = 11.25\%$, since under fixed LGD the systemic losses are defined as $LGD \sum_i w_i \mathbb{1}_i$.

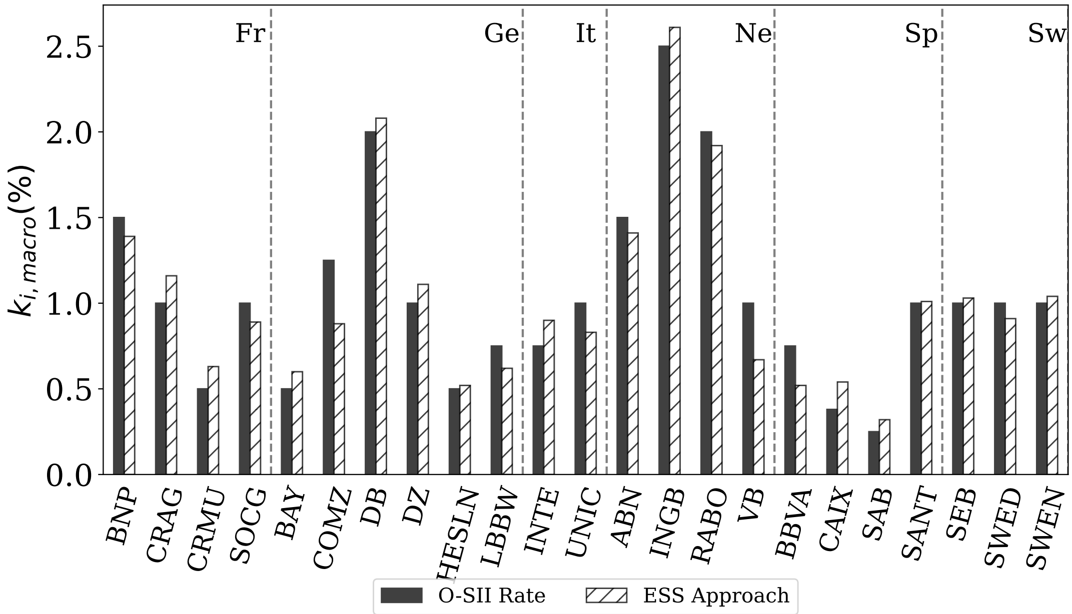
Finally, we need to set λ, which translates systemic financial losses (captured by the ESS estimate) into a consequent GDP loss. We comply with the evidence gathered by Romer and Romer (2017) who reject the hypothesis of a non-linearity, and model λ as a scalar. In our setting, this parameter also allows us to anchor the GDP losses to a realistic baseline figure, overcoming any potential misspecification of the LGD assumption which provides the scale of the ESS figure. To do so, we assume that the baseline figure of GDP losses that the literature estimates, is occurring in a world without macroprudential buffers. Then, we refer to three base cases, which encompass the range of peak-to-through GDP loss estimates, associated with a systemic crisis.[26] We consider three cases, (1) a severe crisis is provided by the estimate of Reinhart and Rogoff (2009) of 9% GDP peak-to-through loss, (2) a moderate crisis at 6%, and (3) a milder crises of 4%, where the last two are estimates from Romer and Romer (2017). Scaling the ESS with micro capital buffers only to that figure, we find the λ estimates provided in Figure 1.

We next implement this model empirically to our universe of European banks. We do this in two steps: First, in Section 5.2.1, we determine the optimal bank-specific macroprudential buffers subject to the current average. In step two in Section 5.2.2 we determine the optimal average buffer using the approach outlined earlier.

[25] Refer to Eurostat's database to source the value of deposit holding institution's liabilities relative to GDP for the countries in the Euro-area, and weight by the relative size of each country.

[26] Cf. Brooke et al. (2015); BCBS (2010) for a review of this literature.

Figure 9: O-SII Buffers vs. Model-Based



Note. This figure shows the 2021 O-SII required rates against the capital requirements based on minimizing the country-specific ESS. The numerical data underlying this figure are given in Table 4 in Annex A.1.

5.2 The Expected Systemic Shortfall Approach: Empirics

5.2.1 Model-Based versus Policy O-SII Rates

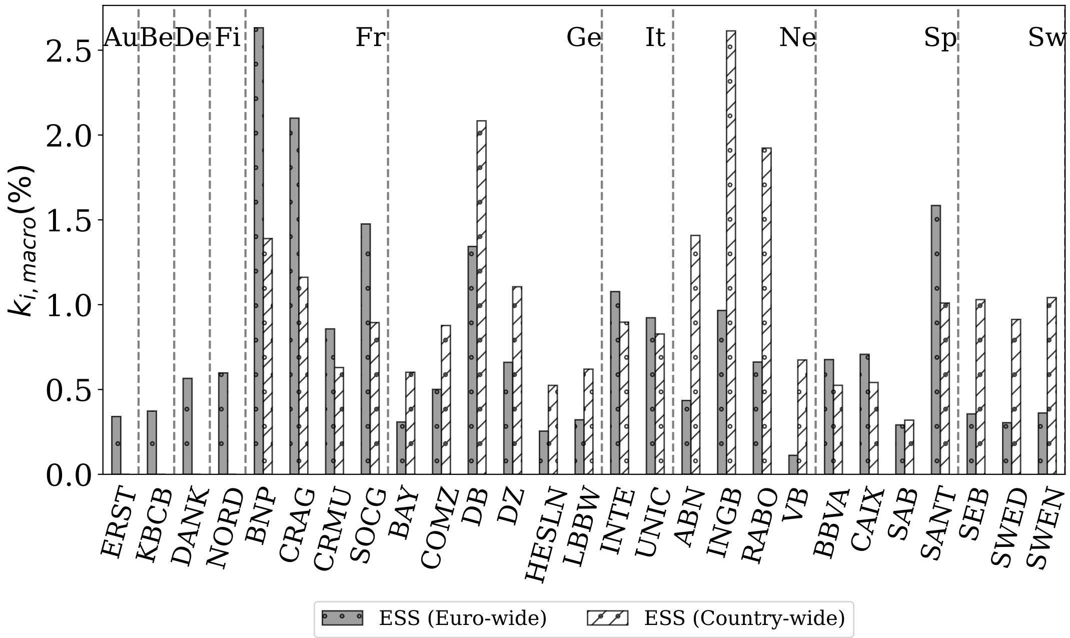
Next we turn to the empirical application of the ESS model established in Section 5.1. We present two approaches. The first is country-specific. We mimic the O-SII framework and calibrate the model separately for each European country in our universe, assuming that local authorities are responsible for setting the policy and that they disregard cross-border correlations. Accordingly, $\overline{k}$ is set equal to the weighted average O-SII rate within the country. In the second approach we take a Europe-wide view and calibrate the model assuming all banks are part of a single system. In the Europe-wide case the buffers take into account cross-country correlations too and $\overline{k}$ is at the European O-SII average.[27]

Figure 9 shows the results of the country-specific case and compares them to the current national O-SII rates. We also include the EEI scores for the banks included. Figure 9 brings out two noteworthy features. First the results of our country-specific

[27]In the country-specific approach we consider only countries with more than one bank in the sample.

case very closely match the O-SII capital buffer rates as they are currently set by local authorities. Apparently local authorities are rather successful in allocating buffers in line with individual banks' contribution to national systemic risk.

Figure 10: Local vs. Euro-Scale Model

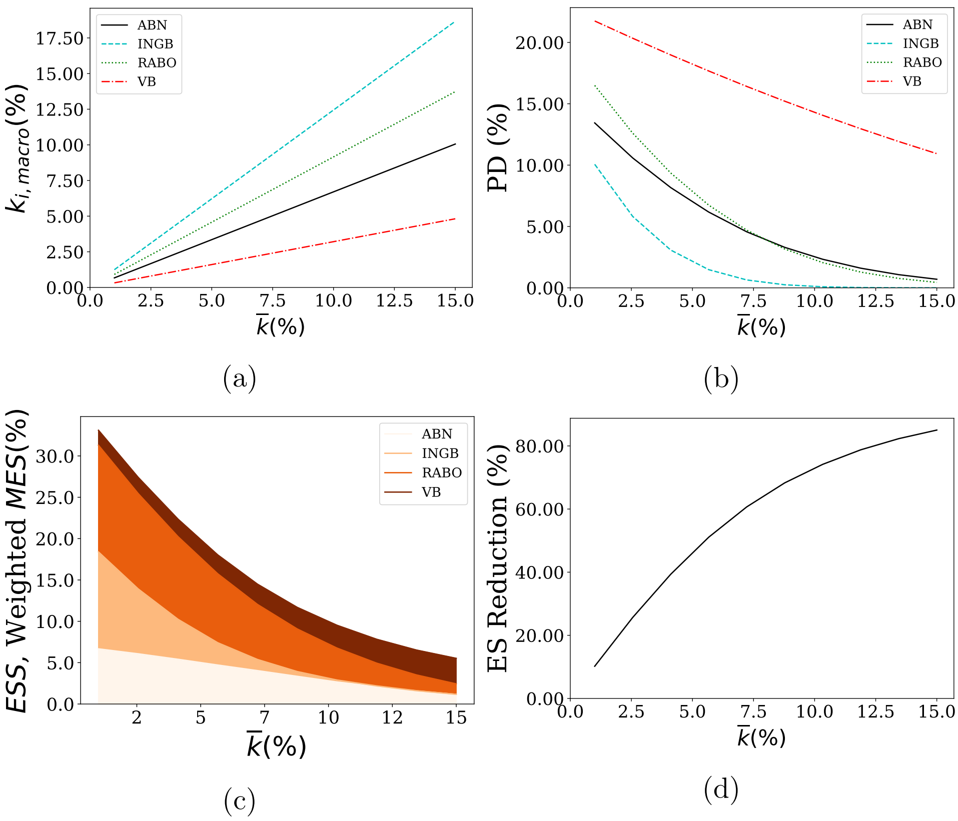


Note. This figure compares the model-based systemic buffers (1) calibrated to a European system, and on the average European O-SII rate (evaluated at 1.25% over the sample); (2) calibrated to the system composed of local banks only, and based on the country average O-SII rate. The model-based capital buffers are evaluated against the average O-SII rate in the sample. The numerical data can be found in Table 4 in Annex A.1.

Figure 10 then compares the ESS approach based on country averages for $\overline{k}$ with the ESS outcomes based on an Europe-wide average buffersize $\overline{k}$. In the Europe-wide case the model consistently prefers to allocate higher buffers to the universe of French banks and to some of the Spanish banks, while it compensates by allocating lower buffers to the Netherlands and Germany. This discrepancy between optimal and actual buffers arises to a much lesser extent when the comparison is with country-specific $\overline{k}$ averages, so it can mostly be attributed to the fact that under the ESS_{local} approach regulators measure the impact of local banks on the local economy only, while under the ESS_{Europe} approach they explicitly take the Euro-wide systemic correlations into account.

Figure 11 below goes a bit further on a smaller group of banks. We carve out from the analysis the four Dutch banks, to illustrate how the choice of $\overline{k}$ affects the optimal solution. In the first panel we can see that the optimal macroprudential requirements increase practically linearly with the relaxation of the constraint (see Fig. 11a); the next panel shows that the default probabilities decrease nonlinearly in $\overline{k}$, reflecting the properties of the conditional density function underlying these measures. (see Fig. 11b).

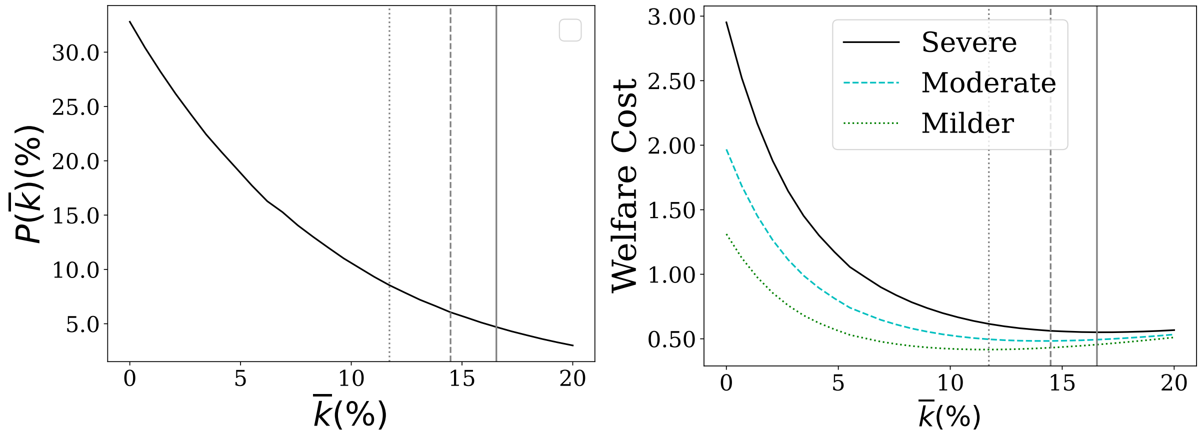
Figure 11: Minimizing ESS, Dutch Sub-sample only



Note. This set of figures shows the level of macroprudential buffers per bank (a), the tolerated default probability (b), and the decline in systemic risk (c) and (d), for a given macroprudential average target add-on.

As indicated in (17), the weighted average MES provides the ESS measure. Figure 11c shows that increasing $\overline{k}$ substantially mostly decreases the risk contributions of the largest banks in the system (INGB, RABO and ABN) while the smaller bank (VB) is not affected significantly. As a consequence, total systemic risk, quantified through the ES of the system, decreases as buffers go up: Figure 11d shows the percentage reduction in ES, measured relative to the case where banks hold only microprudential buffers. These results highlight the importance of the choice of he average buffer target, to which we turn in the next section.

Figure 12: Macroprudential Cost Calibration



(a) (b)

Note. This set of figures shows the calibration of the social disutility function and the resulting optimal $\overline{k}$. Chart (a) shows the risk-neutral probability that a financial crisis occurs when it is defined as bank losses greater than 3% of GDP. Chart (b) shows the resulting welfare cost introducing macroprudential buffers. The model is calibrated for three cases: Severe (9%), moderate (6%) and mild (4%) GDP loss triggered by a financial recession. The grey lines show the optimal macro capital buffers in each case, evaluated at 16.5%, 14.4% and 11.7% respectively.

5.2.2 Social Optimal versus Current Capitalization Rates

Figure 12 shows respectively the estimated probability of a financial crisis (defined as bank default losses exceeding 3% of GDP) as a function of the average macroprudential buffers; and the welfare cost function with the three parametrization scenarios on the severity of the financial crisis. A policymaker pick the level of $\overline{k}$ which minimize the expected cost.

Note the strong convexity of the cost function in each of the parametrizations. As macro buffers are initially introduced, we see a rapid decrease in the cost function. This is due to the high probability of a financial crisis estimated in a system with no macro buffers. As the buffers increase, the probability of a financial crisis decreases and the expected welfare costs given a crisis decrease at the same time. When the size of the buffers increases further, at some point the marginal benefits become smaller and more weight in the cost function is put on the economic cost of maintaining those higher buffers. As a result, the decrease in expected costs slows down and is consequently reversed.

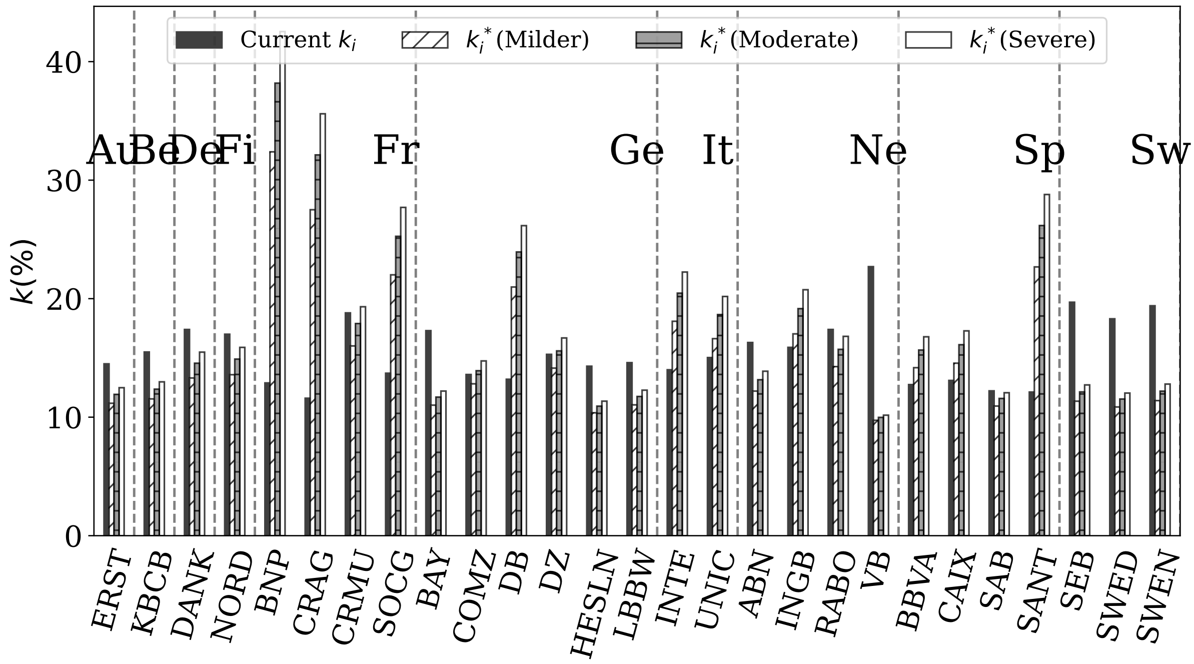
From Figure 12b one can also read the macro buffer average at which W_c is minimized. The higher the expected GDP decline associated with a systemic crisis (modelled through the pass-trough rate λ from financial losses to GDP decline), the higher is the more conservative the policymaker needs to be in lowering the probability of such a crisis, and thus the higher the optimal capital ratio. In the first case (solid black line with severe expected crisis), welfare is optimized at $\overline{k}$ of 16.5%. For a moderate and milder estimate, the optimal value is 14.4% and 11.7% respectively. The expected GDP cost associated with maintaining the optimal buffers is between .5% and .7%, where the output costs are higher in the high buffer case because they are triggered by a much bigger crisis, and at the same time higher buffers are associated with higher credit supply decline by the banks that need to maintain them.

Figure 13 shows the distribution of the total capital buffers from the model across the banks in our European sample, but this time set to an average out to the optimal $\overline{k}$ instead of at the currently actual level. We include three calibration cases and their corresponding optimal average buffer sizes in the sample. We now compare the model outcomes not to the required O-SII buffers (as we did in Figures 9 and 8b) but to the actual total CET1 capitalization, capturing the fact that banks may be subject to additional buffer requirements that were not discussed so far, the countercyclical buffer CCyB and the P2 buffers SyRB[28].

Once again we find some geographical areas where banks seem undercapitalized relative to the model's recommendation and others with apparent overcapitalization compared to the model optimum. The clearest outlier is France, where the model recommends higher capital ratios for all banks in the sample except Crédit Mutuel (CRMU), a coöperative bank. The model output also indicates that Germany's Deutsche Bank (DB) and Spain's Santander (SANT) should have higher capital than they currently have. On the other hand, Dutch and Swedish banks appear to have significantly higher capitalization

[28]See Annex A.2 for details on these policy frameworks.

Figure 13: Model-based optimal capital ratio's (%)



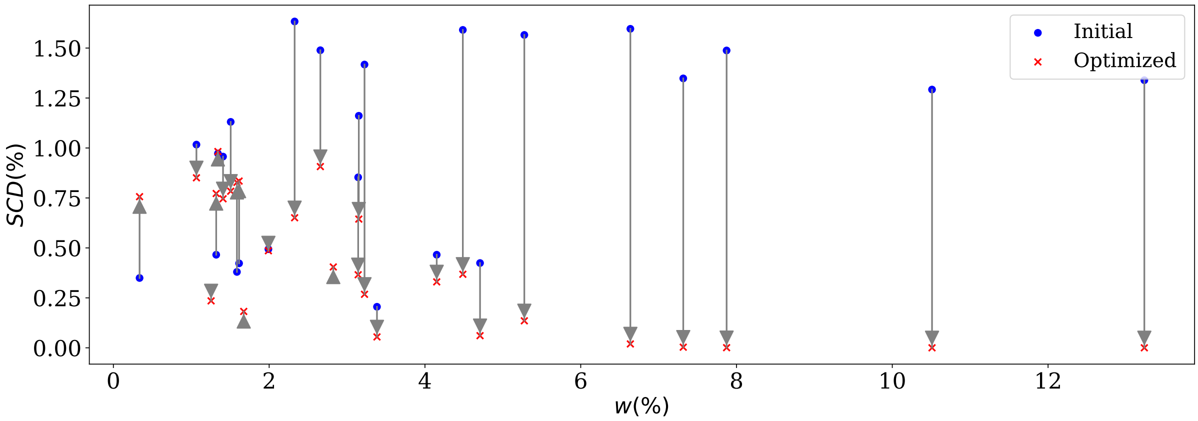
Note. This figure shows the current CET1 capitalization ratios (k_i) vs. the model-based total capital requirements (k_i^*), i.e. the current micro (MCR, CCB, and P2R) plus the model macro requirement, at the socially optimal $\bar{k}$The numerical data underlying this figure are given in Table 4 in Annex A.1.

ratios than required by the model.

The two Italian banks in our sample, Intesa Sanpaolo (INTE) and Unicredit (UNIC), are also highlighed, even though the difference between actual and model outcomes is not that high. Even though the median spread on the Italian banks in our sample appears to be the highest compared to that of other countries throughout the evaluation period (see Chart 16a), the two banks are smaller on a European scale (as Table 2 shows they are less than half the size of BNP for example) which lowers the potential that they will dominate the system and thus lowers the need for larger buffers to control for systemic concerns within Europe.

In Figure 14 we show how the optimized buffers change the impact each bank has on the system. The figure shows two evaluations of the SCD defined in Section 3.6 as a measure of this expected impact. In the first case, we evaluate each bank's SCD with the buffers set at the actual rate as of 2021; and next to it we evaluate the SCD with the optimal level of buffers. The latter obviously lead to much lower values for the *expected* SCD for relatively large banks (i.e. with a large w_i) but actually a lower SCD for smaller banks (with a lower w_i). This illustrates the difference between the EEI and the ESS approaches discussed so far. In the former case, the policimaker seeks to equalize the systemic impact across all banks; while in the later aggregate systemic risk is suppressed by being much stricter with the largest contributors.

Figure 14: Actual vs. Optimized SCD (%)



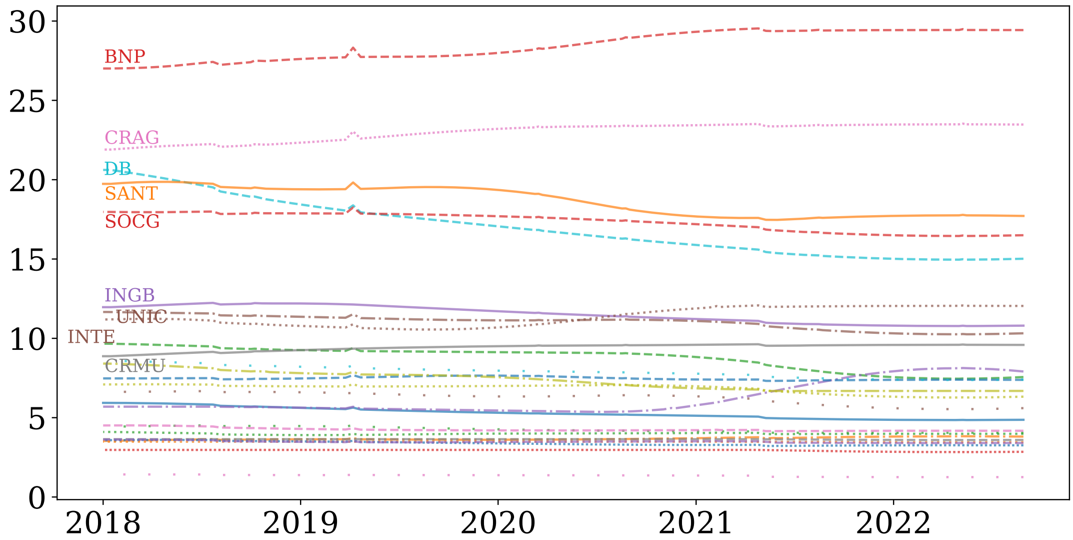
*Note.*This figure shows the SCD value for the banks in our sample in the initial case, i.e. at current capitalization; and in the ESS socially optimal case with the λ_{mod} calibration.

Some have argued against using information derived from CDS prices because the results would be too volatile to be of use in actual regulatory practice. Market data tends to be volatile and the general concern is that this may lead to volatile estimates of the recommended capital ratios. And in fact, changing capital requirements too often may in the long run be counterproductive as banks may become overburdened with satisfying stricter requirements only to see them relaxed after a while.

To address this concern we evaluate the optimal macro requirements, given a socially optimal $\overline{k}$ repeatedly using a rolling estimation approach. This allows us to check the sensitivity of the model calibration to new data coming in. Specifically, we use a window of 156 weeks based on which we optimise the model to determine the appropriate capital buffers for each bank. The window is then shifted one week further over time, after which we again derive the optimal cross-section of the buffers. Figure 15 shows the results.

Unlike what one may have expected, the time series for bank-specific macroptudential buffers are very smooth, the capital buffers do not move erratically with CDS movements; changes happen only gradually and to a minor extent. The fact that weights are part of an inherently nonlinear optimization problem disciplines sudden shifts in PDs in response to actual CDS market movements.

Figure 15: Macroprudential Capital Buffers over Time



Note. This figure shows the rolling-window estimates over time of the socially optimal macro buffers based on the ESS method. $\overline{k}$ is fixed at 14.4%, i.e. the calibration with the λ_{mod} calibration. For clarity we show only the labels of the 10 banks with highest buffer estimates.

6 Conclusions

In this paper we address the problem of calibrating the macroprudential capital buffers of banks. To that end, we develop a novel framework that links systemic risk to the size of the minimum capital requirements. The approach that we develop aims to speak both to academics and regulators.

First, we develop a credit portfolio model, which endogenizes the default thresholds of banks. This makes the model suitable for policy analysis aimed at determining the optimal macroprudential requirements for each bank in the universe considered.

Second, we defined a tail-risk-based measure of the expected cost of default of a systemic institution and applied it to the risk-equalization approach used by regulators to determine systemic buffers in the O-SII and G-SII frameworks. The equalization approach is widely used by regulators, but as we show, in determining the size of the buffers, it is very sensitive to the choice of the reference parameters, such as the size of the non-systemic institution. As a result, going a step further, we embedded the credit model in a portfolio risk framework allowing us to formulate the problem as a risk minimization exercise subject to an average capital buffers target. With this in mind, we show that significant readjustment of the O-SII buffers would occur between countries if the regulation were to be implemented on a European rather than on a domestic scale.

We apply the framework to a universe of 27 large European banks. We use CDS data to infer the default probabilities, asset variances, and default correlations between the different institutions. Using CDS prices rather than equity returns has an important advantage: it allows us to integrate into the analysis systemic banks which are not traded on the equity market. The modeling results show considerable heterogeneity between European countries in the level of current capital requirements relative to the systemic cost different banks pose. We then construct a solution assuming a hypothetical single European regulator who has the authority to set socially optimal buffers for banks in the Eurozone.

Finally, we set up an optimization-based cost/benefit analysis of capital requirements, specifying not just the benefits in terms of reduced contributions to systemic risks, but also the costs of higher capital requirements in terms of reduced credit availability. At the optimum, the first-order condition comes down to equating the marginal costs and marginal benefits of increasing the average macroprudential capital ratio. Consequently, solving for each bank's macroprudential buffer is done in two steps: first, we optimize the average capitalization rate for all the banks in the sample taken together to determine the average macro buffer the financial system should bear. Then we optimize individual banks' macroprudential ratios subject to that average.

Thus we relate the discussion of macroprudential capital buffers to an earlier discussion on the economic cost of capital (BCBS, 2010). We estimate a cross-sectional average of 14.4% macroprudential add-on on top of the microprudential requirements of 4.5% minimum, the 2.5% CCB and the bank-specific P2R CET1 component. This presents a reasonable balance between staving off the materialization of a systemic financial crisis and the cost of inducing a negative lending shock on the economy through the stricter regulation.The average buffer is even higher if one forsees a higher pass-trough from financial losses to GDP decline in a systemic crisis. Again, once the average rate is allocated across the individual European banks in our sample, we see a notable heterogeneity between countries in the gap between their current capitalization and the model-based prescription.

There are several other possible extensions that future research can address. First, the currently proposed portfolio approach could be extended to incorporate specific core-periphery features that have been documented for the financial network in Europe.[29] The addition of a network structure, thus, can foster the causal interpretation of the systemic cost of default estimates that we provide, and could allow for the distinction between banks which are drivers of systemic risk vs. banks which are just sensitive to its materialization from others. Second, one may want to focus on capturing further sources of heterogeneity between banks. For example, it is possible to extend the default model to include types of loss-absorption capacity other than equity, such as subordinated debt or senior unsecured debt. Additionally, one might consider heterogeneity in the lending market as a way of capturing the segmented nature of these markets across Europe, which would allow a more granular view of the social costs of increasing capital buffers across different jurisdictions. Finally, one can also think of an econometric framework that would allow the separation of cyclical vs. structural components of systemic risk, tailoring the size of calibrated buffers more concretely towards structural drivers and reducing any pro-cyclical effects.

Overall, we have provided a flexible modeling basis that can be used as a stepping stone for further discussions on the macroprudential frameworks and on the calibration

[29]Cf. Glasserman and Young (2016); Bräuning and Koopman (2016); Jackson and Pernoud (2021); Andrieş et al. (2022) for arguments and modeling highlights in this direction.

of the size of banks' capital buffers.

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A Appendix

A.1 Input Data

We use data from 27 European banks. The dataset includes weekly CDS prices on subordinate debt provided by Bloomberg; annual end-of-year balance sheet liability size figures; current CET1 capitalization ratios, provided by FactSet; and the banks-specific P2R rates which are publicly available through European regulators.[30] In line with the rest of the buffers in this study, we only consider the CET1 portion of the P2R framework.

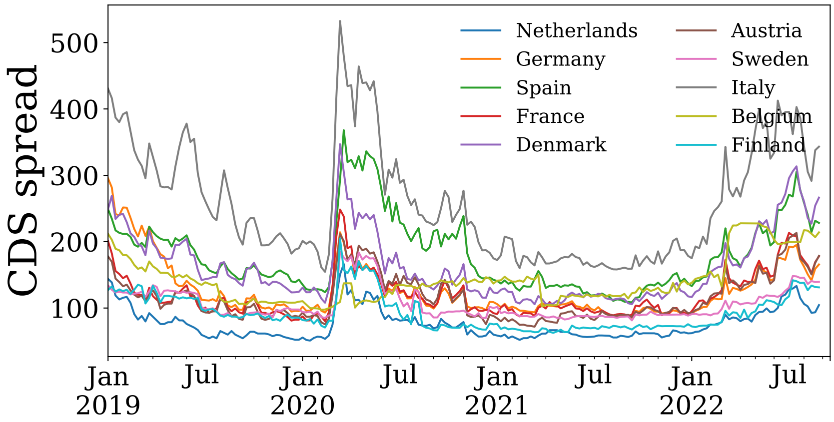
A three-factor latent model is then estimated based on weekly CDS data in the period from August 2019 to August 2022. The use of weekly data allows us to reduce the estimation noise from daily trading and calibrate the model on longer-term spread co-movements. The number of factors were chosen as a scree plot of the Principle Components of the data showed that three latent factors capture more than 80% of the co-variation in the movements of the CDS spreads.

The data encompasses several major tail events for the European economy - the initial Covid shock as of the beginning of 2020 and the first lockdowns, the start of the war in Ukraine with fears of gas shortages as of the beginning of 2022, and the inflation spikes and interest rate tightening by the Fed and the ECB. Figure 16 shows the evolution of the CDS spreads in our sample for the evaluation period.

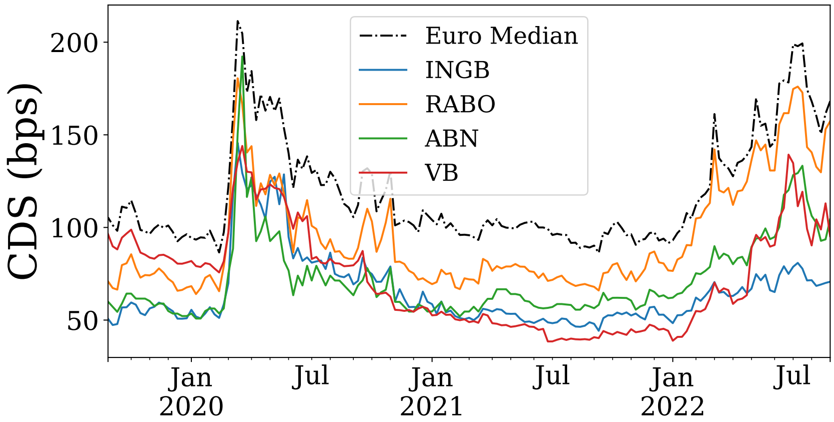
Throughout, we use an LGD assumption of 80% (i.e. ERR of 20%) in line with the prospect provided in Bloomberg of these subordinate CDS. This is a conservative assumption when it comes to extracting the default probabilities from the CDS data, and yet it does not make a difference in the estimation of the EEI-based buffers of Section 4 or the ES buffers of Section 5, as it is assumed to be the same for all banks essentially putting them on the same level playing field with respect to expected losses in default. In the final estimation of the average level of macro buffers (Section 5.1.2) we adjust the passthrough rate (λ) from financial losses to a drop in GDP to make sure that the arbitrary choice of LGD does not affect the evaluation of the expected costs of a financial

[30] See https://www.bankingsupervision.europa.eu/banking/srep/html/p2r.en.html

Figure 16: CDS Prices (bps)



(a) Median Rates per Country



(b) Dutch Banks

crisis for the economy.

The variances of the banks' assets are implied based on the observed CDS rate and capitalization as of August 29th, 2022 using the method outlined in Section 3.2. Table 2 summarizes the input data and the implied model parameters.

A.2 Regulatory Capital Requirements

Here we provide a short overview of the different regulatory capital requirements[31]

[31] For a general discussion see Hull (2018); and for details on the latest implementations and regulatory debates see EBA's guidance on the O-SII framework; ESRB's systemic reports; BIS's guidance on the G-SIB framework.

1. Minimum Capital Requirement (MCR)
   - Pillar 1:
     - Common equity Tier 1 capital (CET1) has to be at least 4.5% of risk-weighted assets (RWA).
     - Total Tier 1 capital at least 6% of RWA.
     - Total (Tier 1 and Tier 2) capital of at least 8% of RWA.
     - Leverage Ratio (Tier 1 Capital/Total Exposure) at least 3%. Total exposure includes on- and off-balance sheet exposure, derivatives exposure, and securities financing transaction exposures. No risk-weighting is applied.
   - Pillar 2 (P2R): bank specific microprudential capital requirement that aims to cover risk which are not (fully) covered by the Pillar 1. Partially satisfied with CET1 capital. Pillar 2 Guidance (P2G) is not legally binding but may have implications on the distributional capacity to shareholders.
2. Combined Buffer Requirement (CBR)
   - Capital Conservation Buffer (CCB) (Basel III) to be maintained in normal times. If levels fall below requirements, banks restrain dividends and bonus payments until capital has been replenished. CET1 add-on of 2.5% of RWA.
   - Countercyclical Capital Buffer (CCyB)
     - Applied country-wide. Similar to CCB but at the discretion of national authorities. It is a CET1 add-on of between 0% and 2.5% of the bank's domestic RWAs.
   - Systemic risk buffer (SyBR)
     - Additive to other buffers. Designed to address risk spillover from the economy (from the system) to individual banks.
     - At the discretion of national authorities aiming to address risks that are not covered by the CCyB or the G-SII/O-SII buffers.

  - May apply to all banks, particular individual banks, and across a subset of exposures (e.g. on the residential exposure of the RWAs as in e.g. Belgium, Germany, etc.).

- Global Systemically Important Institution (G-SII) buffers on Globally Systemically Important Banks (G-SIBs):
  - Part of the combined buffer requirement. Typically ranging between 0% and 2.5%.
  - Designed to address negative spillovers from individual banks to the global economy.
  - Framework and assessment methodology set by the Basel Committee on Banking Supervision (BCBS) and applies to banks globally (ranking in categories based on size, complexity, cross-jurisdictional activity, interconnectedness, substitutability of activities)
  - Enforced by national authorities.
- Other Systemically Important Institution (O-SII) buffers
  - Part of the combined buffer requirement. Typically ranging between 0% and 3%, where the maximum of G-SII and O-SII applies.
  - National authorities have the discretion on the size of the buffer surcharge.
  - Designed to address negative spillovers from individual banks to the national economy.
  - Guidelines set by European Banking Authority (EBA) (ranking in categories based on size, importance, complexity, and interconnectedness).
  - Measurements and enforcement by national authorities on a "comply or explain" basis.

A.3 Latent Factor Model Estimation

On a given day we don't observe the market value of a bank's assets, but we observe how far it is from the default threshold. This is implied by the default probability associated with the market price of a CDS contract traded, such that

$$PD_{i,t} = \mathbb{P}(V_{i,T} \leq D_i) = \mathbb{P}(U_i \leq -DD_{i,t}) = \Phi(-DD_{i,t})$$

where $\Phi(.)$ is the cumulative standard normal distribution, and t are periodic observations of the default probability, in our case with weekly frequency. This implies the DD measure at the end of the trading week

$$DD_{i,t} = -\Phi^{-1}(PD_{i,t}) \tag{21}$$

Observed changes in the default probability can then be linked to the changes in the asset value by first-differencing (21) and relating it to (4):

$$\Delta\Phi^{-1}(-PD_{i,t}) = \Delta DD_{i,t} = \frac{\ln V_{i,t} - \ln V_{i,t-1}}{\sigma_i\sqrt{T-t}} \tag{22}$$

More importantly, this allows us to infer the correlation structure between the latent default variables. For example, the correlation between banks i and j can be written as

$$\mathbb{Corr}(U_{i,t}, U_{j,t}) = \mathbb{Corr}(\Delta DD_{i,t}, \Delta DD_{j,t}) \equiv a_{i,j} \tag{23}$$

Based on these observed correlations, we can construct the target correlation matrix towards which to fit the latent factor model of (9) as

$$\Sigma \equiv \begin{bmatrix} 1 & a_{12} & a_{13} & \dots & a_{1N} \\ a_{21} & 1 & a_{23} & \dots & a_{2N} \\ \dots & \dots & \dots & \dots & \dots \\ a_{N1} & x_{N2} & x_{N3} & \dots & 1 \end{bmatrix} \tag{24}$$

The parameters of (9) can then be estimated by minimizing the sum of squared differences between the observed correlations above and the factor-model implied correlations:

$$\min_{\rho_i,\ldots,\rho_j} \sum_{i=2}^{N}\sum_{j=1}^{N}(a_{ij} - \rho_i\rho_j')^2 \tag{25}$$

A.4 Inferring PDs from observed CDSs

We infer the banks' default probabilities from single-name CDS close prices using the approach outlined by Duffie (1999). It is based on the simplifying assumption that recovery rates (RR) are known and constant over the horizon of the contract.[32]

With this in mind, we can proceed with identifying the equation for pricing a CDS contract. By market convention, at the initiation date t of the contract the spread CDS_t is set to ensure that the value of the protection leg and the premium leg of the contract are equal, such that the contract has a zero value:

$$\underbrace{CDS_t \int_t^{T_{cds}} e^{-r_\tau \tau}\Gamma_\tau d\tau}_{\text{PV of CDS premia}} = \underbrace{(1 - ERR_t)\int_t^{T_{cds}} e^{-r_\tau \tau} q_\tau d\tau}_{\text{PV of protection payment}} \tag{26}$$

where T_{cds} is the maturity date of the CDS contract, $\tau > t$ is future time after the initiation of the contract, r_τ is the annualized instantaneous risk-free rate, CDS_t is the observed CDS spread for the day, q_τ is the annualized instantaneous risk-neutral default probability , $\Gamma_\tau = 1 - \int_t^\tau q_s ds$ is the risk-neutral survival probability until time τ, and ERR_t is the expected recovery rate in case of default, assumed to be constant over time.

For simplicity, we assume that the yield and the probability default curves are flat over the lifetime of the CDS contract once the contract is established. Then, we can set $r_\tau = r_t$ and $q_\tau = q_t$ over the lifetime of the contract initiated at time t. Then the default

[32]We do not try to identify expected recovery rates separately from the observed CDS data. There are alternative and more sophisticated approaches (cf Pan and Singleton (2008); Christensen (2006); Acharya and Johnson (2005); Duffie and Singleton (1999)). However, given the identification challenge between PDs and RRs, the simplifying assumption we employ in estimation is widely used in the literature and is difficult to improve.

probability q at time t follows from equation (26):

$$q_t = \frac{aCDS_t}{a(1 - ERR_t) + bCDS_t} \tag{27}$$

with $a = \int_t^{T_{cds}} e^{-r\tau} d\tau$ and $b = \int_t^{T_{cds}} \tau e^{-r\tau} d\tau$. Setting $T_{cds} - t = 5$ to capture 5-year CDS contracts, we can imply the annualized default probabilities.

A.5 Model Outcome Tables

Table 2: Model Input Data

Country	Code	Name	w_{euro}	w_{local}	$CDS(bps)$	$PD(\%)$	ρ_1	ρ_2	ρ_3	$\hat{\sigma}(\%)$	k_{CET1}	k_{P2R}
Austria	ERST	Erste Group	1.51	100.00	79.80	2.12	0.92	0.02	0.03	7.81	14.50	0.98
Belgium	KBCB	KBC	1.67	100.00	214.03	2.51	0.16	0.14	(0.14)	8.66	15.50	1.05
Denmark	DANK	Danske Bank	2.66	100.00	266.43	3.08	0.95	0.10	0.10	10.21	17.40	1.01
Finland	NORD	Nordea	2.82	100.00	131.16	1.58	0.60	(0.70)	0.19	8.72	17.00	0.98
France	BNP	BNP Paribas	13.24	37.59	163.10	1.94	0.96	0.20	0.06	6.81	12.89	0.74
	CRAG	Credit Agricole	10.51	29.85	156.92	1.87	0.95	0.22	0.07	6.08	11.60	0.84
	CRMU	Credit Mutuel	4.15	11.79	206.83	2.43	0.51	0.08	(0.05)	10.53	18.80	0.98
	SOCG	Societe Generale	7.32	20.78	192.76	2.27	0.94	0.18	0.06	7.48	13.71	1.19
Germany	BAY	Bayern LB	1.34	8.43	64.24	1.94	0.91	(0.08)	0.02	9.23	17.30	1.13
	COMZ	Commerzbank	2.33	14.61	317.91	3.62	0.95	0.17	(0.01)	8.22	13.60	1.13
	DB	Deutsche Bank	6.64	41.68	328.06	3.72	0.92	0.14	(0.08)	8.03	13.20	1.41
	DZ	DZ Bank	3.14	19.74	49.95	1.78	0.85	0.00	0.10	7.99	15.30	0.96
	HESLN	Helaba	1.07	6.70	69.33	2.00	0.92	(0.07)	0.08	7.61	14.30	0.98
	LBBW	LBBW	1.41	8.84	51.96	1.80	0.90	(0.03)	0.08	7.63	14.60	1.03
Italy	INTE	Intesa Sanpaolo	5.28	54.04	323.84	3.68	0.91	0.14	0.05	8.51	14.00	1.01
	UNIC	Unicredit	4.49	45.96	362.50	4.07	0.92	0.12	0.02	9.38	15.03	0.98
Netherlands	ABN	ABN Amro	1.99	19.54	104.46	1.26	0.73	0.01	(0.26)	8.03	16.30	1.13
	INGB	ING	4.71	46.22	70.71	0.86	0.75	(0.07)	0.10	7.37	15.89	0.98
	RABO	Rabobank	3.15	30.94	157.35	1.88	0.95	0.15	0.07	9.23	17.40	1.07
	VB	Volksbank	0.34	3.30	95.29	1.16	0.65	0.10	(0.21)	11.28	22.70	1.69
Spain	BBVA	BBVA	3.22	20.49	230.76	2.69	0.94	0.17	(0.02)	7.20	12.75	0.84
	CAIX	Caixabank	3.38	21.51	225.64	2.64	0.19	(0.09)	(0.51)	7.37	13.10	0.93
	SAB	Sabadell	1.25	7.97	365.34	4.10	0.31	(0.10)	(0.64)	7.62	12.22	1.21
	SANT	Santander	7.87	50.03	214.60	2.51	0.96	0.16	(0.00)	6.74	12.12	0.84
Sweden	SEB	Skandinaviska EB	1.59	35.09	139.54	1.67	0.64	(0.71)	0.03	10.30	19.70	1.01
	SWED	Swedbank	1.32	29.20	164.63	1.96	0.65	(0.38)	(0.25)	9.81	18.30	1.01
	SWEN	Handelsbanken	1.61	35.70	133.98	1.61	0.67	(0.63)	0.06	10.06	19.40	1.01

Note. This table shows the banks in our analysis universe, their relative size, CDS spreads as of the evaluation date, implied PD, the implied st. dev. of thier assets, the estimated factor model loadings, total CET1 capitalization ratio, and the P2R capital requirement. The two columns w_{euro} and w_c show the liability size of the institutions on a European and on a domestic scale, repsectively.

Table 3: Model Output: EEI Approach

		k_{macro} (%)			$PD(k_{macro})$			$SCD(k_{macro})$		
Country	Bank	1%	5%	10%	1%	5%	10%	1%	5%	10%
France	BNP	10.46	7.47	5.92	0.18	0.84	1.69	0.13	0.63	1.26
	CRAG	8.37	5.66	4.34	0.20	0.92	1.75	0.13	0.63	1.26
	CRMU	14.76	9.75	7.06	0.82	3.59	6.74	0.13	0.63	1.26
	SOCG	11.25	7.86	6.18	0.22	1.07	2.09	0.13	0.63	1.26
Germany	BAY	14.16	10.14	8.10	0.36	1.62	3.06	0.13	0.63	1.26
	COMZ	12.67	9.07	7.38	0.26	1.21	2.24	0.13	0.63	1.26
	DB	12.70	9.20	7.47	0.18	0.89	1.74	0.13	0.64	1.26
	DZ	11.91	8.40	6.54	0.31	1.40	2.74	0.13	0.63	1.26
	HESLN	10.73	7.32	5.58	0.36	1.60	3.03	0.13	0.63	1.26
	LBBW	10.68	7.36	5.59	0.37	1.57	3.00	0.13	0.63	1.26
Italy	INTE	13.89	10.28	8.31	0.21	0.99	2.01	0.15	0.75	1.50
	UNIC	15.63	11.64	9.70	0.24	1.12	2.13	0.15	0.75	1.50
Netherlands	ABN	10.79	6.94	4.94	0.51	2.32	4.43	0.15	0.74	1.47
	INGB	10.75	7.54	5.91	0.27	1.21	2.31	0.15	0.74	1.47
	RABO	14.44	10.55	8.42	0.33	1.44	2.82	0.15	0.74	1.47
	VB	13.13	7.22	4.29	1.68	6.94	11.98	0.15	0.74	1.47
Spain	BBVA	10.62	7.29	5.67	0.26	1.24	2.38	0.11	0.55	1.10
	CAIX	9.57	5.95	4.11	0.50	2.32	4.41	0.11	0.55	1.10
	SAB	8.12	4.05	1.88	1.06	4.66	8.72	0.11	0.55	1.10
	SANT	10.32	7.22	5.69	0.16	0.84	1.69	0.11	0.55	1.10
Sweden	SEB	17.21	12.71	10.39	0.28	1.38	2.73	0.17	0.87	1.74
	SWED	15.37	10.81	8.49	0.38	1.89	3.67	0.17	0.87	1.74
	SWEN	16.55	12.26	10.00	0.30	1.39	2.73	0.18	0.87	1.74

Note. This table shows the optimal buffers based on the EEI Approach. We show the estimated macro-prudential capital buffers and the resulting risk-neutral default estimates for the individual banks. The results are shown for reference bank size of 1%, 5% and 10% relative to the total size of the banking sector. The results are estimated on a local country scale. For the reference bank in each country, we assume the LGD follows the standard assumption. The variance of the reference bank's assets is assumed to be the average of the asset variances for all banks in that country.

Table 4: ESS Approach: Model Output Data

			$\overline{k}$ =O-SII Average			$\overline{k}$ = Social Optimum			
Country	Names	O-SII	$\overline{k}^{osii,loc}$	$k_{i,macro}^{loc,osii}$	$k_{i,macro}^{eur,osii}$	CET1r	k_{mild}^*	k_{mod}^*	k_{severe}^*
Austria	ERST	1.00		0.34		14.50	11.17	11.92	12.49
Belgium	KBCB	1.50		0.37		15.50	11.54	12.36	12.98
Denmark	DANK	3.00		0.57		17.40	13.31	14.55	15.49
Finland	NORD	2.00		0.60		17.00	13.58	14.90	15.89
France	BNP	1.50	1.13	2.63	1.39	12.89	32.39	38.19	42.54
	CRAG	1.00	1.13	2.10	1.16	11.60	27.50	32.13	35.60
	CRMU	0.50	1.13	0.86	0.63	18.80	16.01	17.90	19.32
	SOCG	1.00	1.13	1.48	0.89	13.71	22.01	25.26	27.70
Germany	BAY	0.50	1.36	0.31	0.60	17.30	11.01	11.69	12.20
	COMZ	1.25	1.36	0.50	0.88	13.60	12.82	13.92	14.75
	DB	2.00	1.36	1.34	2.08	13.20	20.98	23.94	26.16
	DZ	1.00	1.36	0.66	1.11	15.30	14.14	15.59	16.69
	HESLN	0.50	1.36	0.25	0.52	14.30	10.37	10.93	11.35
	LBBW	0.75	1.36	0.32	0.62	14.60	11.04	11.75	12.28
Italy	INTE	0.75	0.86	1.08	0.90	14.00	18.09	20.47	22.25
	UNIC	1.00	0.86	0.92	0.83	15.03	16.63	18.66	20.18
Netherlands	ABN	1.50	2.10	0.44	1.41	16.30	12.20	13.16	13.88
	INGB	2.50	2.10	0.97	2.61	15.89	17.03	19.16	20.75
	RABO	2.00	2.10	0.66	1.92	17.40	14.27	15.73	16.82
	VB	1.00	2.10	0.11	0.67	22.70	9.74	9.98	10.17
Spain	BBVA	0.75	0.75	0.68	0.52	12.75	14.18	15.67	16.78
	CAIX	0.38	0.75	0.71	0.54	13.10	14.55	16.11	17.28
	SAB	0.25	0.75	0.29	0.32	12.22	10.94	11.58	12.06
	SANT	1.00	0.75	1.58	1.01	12.12	22.68	26.17	28.79
Sweden	SEB	1.00	1.00	0.36	1.03	19.70	11.35	12.13	12.72
	SWED	1.00	1.00	0.30	0.91	18.30	10.86	11.53	12.03
	SWEN	1.00	1.00	0.36	1.04	19.40	11.40	12.20	12.79

Note. This table shows the optimal buffers based on the ESS model output. The columns show for each bank in the universe the regulatory O-SII macroprudential capital buffers for 2022; the country weighted average, $\overline{k}^{osii,loc}$: the optimal buffer rate at country scale calibrated to the country O-SII average; $k_{i,macro}^{eur,osii}$: the optimal buffer rate at European scale, calibrated to the European O-SII average of 1.25%.