Macroprudential Regulation: A Risk Management Approach*

Job Market Paper (Daniel Dimitrov)

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Abstract

We address the problem of regulating the size of banks' macroprudential capital buffers by using market-based estimates of systemic risk and by developing a modeling mechanism through which capital buffers can be allocated efficiently across systemic banks. First, a Distance-to-Default type measure relates a bank's default risk to its capital requirements. Second, a correlation structure in the default dependencies between banks is estimated from co-movements in the single-name CDS spreads of the underlying banks. Third, risk minimization and equalization approaches are adopted to allocate the capital requirements in line with a policy which balances the social costs and benefits of higher capital requirements. The model is applied to the European banking sector.

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1 Introduction

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 their most 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]

Following EBA guidelines targeting the identification of globally and domestically important banks (G-SIBs and D-SIBs, repsectively), Central Banks rely on assigned regulatory scores as a measure of systemic impact based on size, interconnectedness with the rest of the financial system, substitutability in the lending market, complexity and cross-border activity. Based on their overall ranking score, banks are allocated to buckets with corresponding add-on requirements on the minimum loss-absorbing capacity they should hold.[2]

However, there exists very little theoretically backed guidance on how to calibrate these macroprudential buffers. This not only makes it difficult to assess the adequacy of macroprudential buffers in any given country but has also led to buffers of widely diverging stringency across countries. For want of a generally accepted basic framework, aligning these diverging approaches has proven to be difficult.[3]

On the academic forefront, there is a vast and growing literature on measuring systemic risk and assessing the contribution that individual banks make to it by deriving correlation and tail dependencies from asset prices. This literature leverages market data for evaluating the contributions and sensitivities of individual banks to systemic shocks (Leland, 1994; Segoviano and Goodhart, 2009; Zhou, 2010; Huang et al., 2012; Adrian and Brunnermeier, 2016; Acharya et al., 2017). Still, there is, to the best of our knowledge, currently no approach that can provide guidance on how high capital buffers should be based on the observed measure of systemic importance that these approaches offer.

At the same time, there is an extensive academic literature on macroprudential policy. Its focus, however, is almost exclusively on that other mainstay of macroprudential policies, interventions aimed at limiting household leverage in the mortgage market, 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'

[1] Cf. ESRB (2021).

[2] Cf. EBA (2020); ESRB (2017).

[3] ESRB (2017) recognizes that the majority of countries use a bucketing approach, but the numbers of buckets and the methods for their classification differ. In all calibration approaches examined by the ESRB, the discretionary choice of parameters and assumptions affects the final calibration of the buffers significantly. For example, even though an equalizing approach, 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), tends to be the favored method by most regulators, the assumptions and parameter choice behind the methodology have been very diverse across countries in their implementation.

microprudential capital as a way of internalizing the implicit costs these institutions pose on the financial system.

We address the gaps by using market-driven estimates of systemic relevance implied by asset pricing theory and on this basis develop a quantitative framework that provides capital buffer add-on recommendations. Methodologically, we rely on credit risk approaches to quantify the probability of multiple defaults happening at the same time. It should be noted that this is not entirely disconnected from 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, in line with Dimitrov and van Wijnbergen (2022), we break away from the use of equity return data to assess distress dependencies. Using equity returns dominates the systemic risk measurement literature (Adrian and Brunnermeier, 2016; Acharya et al., 2017), but at least in Europe the presence of privately held, state-owned, and/or coöperative banks rules out this channel of inferring asset correlations. Instead, we rely on market data from CDS contracts where most key European banks are traded to extract the required information on covariance structure.

There are several key mechanisms behind our approach. First, we use a default threshold approach to relate the default risk of a single bank to its capital requirements. This follows from Merton (1974)'s observation that equity under limited liability is in fact a call option on the assets of the firm, as default occurs when the market value of the firm's assets falls below the face value of its debt. Developing the argument a step further, we relate analytically the default probability to the ratio of common equity to debt that banks are required to hold. By requesting higher capital buffers, regulators force individual banks to deleverage and make banks safer.

Second, as a measure of systemic risk exposure, we look at the propensity of multiple banks to default at the same time. We rely on a Vasicek-type factor model typically used for the estimation of the risk of a portfolio of loans. In this approach, a set of common factors across all banks drives the common variation in their creditworthiness. The individual exposure of banks to the market factor (or factors) will determine the degree to which their risk is driven by the market and the degree to which it is idiosyncratic. Time co-variation in the single-name CDS spreads of the underlying banks allows us to estimate these factor exposures.

Third, we develop two approaches to map measures of systemic importance into add-on macroprudential buffers. The first one buillds on the *Equal Expected Impact* (EEI) approach through which supervisors aim at equalizing the expected default loss between systemic institutions and a non-systemic reference bank.[4]. But we develop an alternative to the scoring methodologies employed in the G-SIB and D-SIB frameworks for this EEI approach, an alternative that is based on market prices rather than on accounting information. 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

[4]Cf. EBA (2020) for a brief overview of the approach and ESRB (2017) for an international comparison of its application.

buffers lowers its own expected default costs, and at the same time lowers the component of its social costs associated with other banks in the system failing at the same time. We interpret this as a positive safety spillover effect from the introduction of macroprudential buffers. We show how using this new measure allows application of the EEI approach to be fully based on information embedded in market prices.

The EEI approach is widely used but it does have its shortcomings as we demonstrate in what follows. In particular, the mapping from scores to buffers that results depends on the reference institution chosen and the weight this institution gets assigned. In our suggested alternative approach, we formulate the capital calibration problem 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 in our optimization based approach is related to the approach 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 approach one step further however by also showing how the average can be calibrated as well: in the second step we derive the target rate from a trade-off between the reduced expected costs of distress through higher loss-absorbing capacity that a higher average buffer gives, against the expected loss of output through reduced availability of bank credit that it also leads to.

This paper continues as follows: Section 2 discusses the relation of our study to the wider literature; 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 Dutch financial system; 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, applying the method empirically on a European dataset; and finally Section 6 concludes.[5]

2 Relation to the Literature

This paper connects several disparate strands of the literature.

First of all, we build on the literature on quantifying 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 models developed in this area are largely model-free in the sense that they do not rely on specific assumptions on the structure of markets, 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

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

dependence.[6]

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). The philosophy we adopt is that for a regulator, the universe of banks relevant to the local economy can be considered as a portfolio of long loan positions, where the liabilities of each bank represent the size of an individual loan. From that point of view, we relate closely to studies quantifying systemic risk through a similar collateralization approach as Huang et al. (2012); Puzanova and Düllmann (2013). In these cases, systemic losses occur when an institution defaults and cannot cover the value of its liabilities. The tendency of particular institutions to produce systemic losses then will result in a higher contribution to systemic risk.

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

At the same time, we relate also to the literature evaluating long-term economic impact of capital buffers. One major strand of the literature tries to equate the marginal social costs of raising buffers with the social costs of having to raise more capital. This is often done 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 advantage on 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 capital requirements would first of all 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

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

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 on 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 5.3, we rely on quantifying the short term effects from higher macroprudential capital requirements on the size of the aggregate lending stock that have been document more clearly 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. As a result, 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.).

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 it 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 any change in the cost of capital when capital buffers change, we directly look at estimates on the lending reduction 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 quantifying 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 with higher buffers.

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, we consider banks' default risk in isolation and in Section 3.4 we lay the foundation of distress correlations.

3.1 Financial Distress, Capital Requirements and the Default Threshold

Assume that a stochastic latent variable U_i governs an individual bank's creditworthiness, but is not directly observable by the bank's depositors or the regulator. $i \in (1, \ldots N)$ is a bank indicator in a financial system of N banks. By assumption, U_i follows a standard normal distribution. A higher realization of U_i indicates a better state of nature and consequently a lower default probability over the coming one-year period.

The model can easily be generalized to incorporate a non-Gauss distribution for U_i, allowing for example for fat-tails or skew as 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 parametric model with more moments becomes difficult to justify. For this reason, we continue here with the standard Gaussian framework. It is worth noting that even if the default of individual banks is Gaussian, the aggregated losses generated for the system will not be, as we show in Section (3.5).[7]

Now assume that default occurs if the latent variable with $U_i \sim N(0,1)$ falls below a threshold X_i. This leads to the following default indicator function:

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

Next, we relate the default threshold to the capital ratio of a bank. This will allow us to measure the effect of capital regulation on banks' default probability. Before doing that we need to flesh out the structure of the basic Merton model we use to model an individual bank. Assume then that the (unobserved) market value of banks' aggregate risk-weighted assets $V_{i,t}$ follow 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.

In Merton's setting, default occurs at maturity (time $t+T$) when $V_{i,t+T}$ falls below a fixed default threshold D_i. We can then write the default probability for the bank as

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

[7]See Bolder (2018); McNeil and Embrechts (2005) for the class of default threshold models commonly utilized in the credit risk literature and in practice.

Consider next the well-known concept Distance to Default DD_t:

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

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

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

This implies that the term $\frac{W_{t+T}}{\sqrt{T}}$ can be interpreted as the latent creditworthiness variable U_i in Equation (1). Similarly, the default threshold X_i becomes equivalent to the negative of Merton's DD. In this way, the default threshold that we defined loosely in (1) now receives a concrete form through 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.[8] As a simplifying approximation, we abstract from debt maturity complications and assume all bank debt is short-term, as is the case with the dominant liability of most banks, call deposits. Since equity is the asset value net of debt ($E_i = V_i - D_i$), the capital capital ratio can be written as

$$k_i = \frac{E_i}{V_i} = \frac{V_i - D_i}{V_i} \implies \frac{V_{i,t}}{D_i} = \frac{1}{1 - k_i}$$

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

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

As a result, combining (1) and (5) we can derive a relationship between the default probability over a year from now and the current capitalization ratio:

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

3.2 Implying Banks' Asset Variances

Relationship (6) is useful in two ways. First, it provides the default probability which a regulator can 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 target the default probability by setting minimum capital requirements k_i, the regulator needs to know the bank's 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.

[8] In the $T = 1$ assumption, we follow the interpretation that T represents the time until the next audit of the bank, a year from the evaluation date as in Lehar (2005), which makes a pronouncement if the bank meets regulatory capital requirements.

To do so, first we need to extract the current default probabilities from the observed CDS market prices. In the process, we use 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.[9][10]

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 then write the implied volatility derived from (6) 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 $\hat{\sigma}_{i,t}(k_{i,t}, PD_{i,t})$ and k_i for three different levels of the default probability. Each upward-sloping line traces out $\hat{\sigma}_{i,t}(k_{i,t})$ as a function of k_i for a specific value of $PD_{i,t}$. 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 3 in the Annex shows the implied asset standard deviations for the European sample of banks used in the consequent empirical analysis.

3.3 Micro and Macroprudential Capital

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:

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

The micro component can be seen as the minimum regulatory requirement which holds for all banks. The macro component is a capital buffer requirement that targets specifically banks identified as systemic (or systemically Important) institutions.

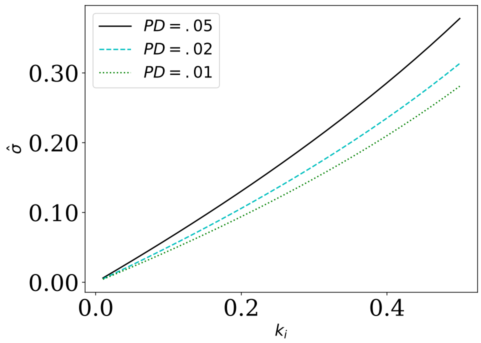
A regulator thus is responsible for safeguarding financial stability by, within certain constraints, proactively managing the lower bound of the capital buffers which individual

[9] Appendix D provides the details behind this CDS pricing formula.

[10] 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 asset composition of the systemic institutions, about the expected recovery rate; Huang et al. (2009) set it to 55%; Huang et al. (2012) calibrate the ERRs to Markit survey data and show that they exibit very little time variation, staying mostly between 20-30%.

[10] 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.

Figure 1: Implied RWA Volatility



Note. This figure shows the relationship between bank capitalization and asset variance for varying degrees of observed default probability.

banks need to satisfy. We take the current minimum microprudential ratio k_{micro} as a given, as its analysis is outside the scope of the regulatory task that we consider here.[11] Within this setting, the regulator only needs to determine the required minimum $k_{i,macro}$ for each systemic bank in order to curb systemic risk.

More specifically, we will assume that k_i corresponds to Common Equity Tier 1 capital (CET1), as the main going concern capital ratio in the Basel III framework corresponding to the way microprudential and macroprudential requirements are set, as explained in Annex (B). Furthermore, we abstract from the various types of equity and assume that CET1 is a good representation of a bank's equity. This is in line with viewing CET1 as the key component of going concern equity.

Going forward, we take a two-step approach. In the first step, we derive the implied variance structure of the risk-weighted assets portfolio's of all banks from observing their current capital ratio and current default probability. In a second step then, 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 van Wijnbergen (2013). Assuming that the minimum requirements are binding, we put all banks on an equal footing and vary the required buffers above the minimum capital requirement and the capital conservation buffer.

3.4 Banks' Asset Correlations

Up to this point, 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 the 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 (Cf. Pascual et al. (2006)).

Formally, we can write:

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

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

where $M = [m_1, \dots m_f]'$ is the vector of f common latent factors, and 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.[12] 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.

Note that if we assume a single common factor and the same factor exposure across all banks we get the well-known Vasicek loan portfolio model as a special case. 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 Appendix C we discuss the estimation procedure of the Gaussian factor model with a correlation matrix which itself is estimated from default probability time series implied by the observed CDS spreads. Finally, Table 3 in the Annex shows the fitted model exposures the European sample of banks. This will be one of the key inputs in the consequent systemic risk analysis.

3.5 Systemic Costs of Default

Next, we construct a measure of the Systemic Cost of Default (SCD) of a bank. The measure encompasses the expected losses in case of default of the bank as special cases, 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 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 costs*), plus (b) the additional losses of all other banks conditional with bank i's distress, to the extent that their losses exceed their *unconditional* expected costs of distress. We label the latter term *indirect costs*.

Formally, define $PD_{j|i} \equiv \mathbb{E}(\mathbb{1}_j | \mathbb{1}_i = 1)$ as the conditional default of bank i, given that bank j defaults, and denote LGD_i as the loss given default of bank i, and w_i as the liability weight of the bank in the systemic portfolio.In the credit risk space, w_i corresponds to the Exposure at Default (EAD) of the bank. Then, we can write the suggested systemic loss function as:

[12] 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. Cf. 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.

$$SCD_i = \underbrace{w_i LGD_i PD_i}_{\text{Direct Cost (Microprudential)}} + \underbrace{\sum_{j \neq i} w_j LGD_j \left(PD_{j|i} - PD_j\right) PD_i}_{\text{Indirect Cost (Macroprudential)}} \tag{10}$$

The expression above illustrates clearly how microprudential regulation directly targets the own default for bank i, while macro-prudential acknowledges the fact 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. So here too we get that if defaults are uncorrelated we have that $PD_{j|i} = PD_j$, and the macro-prudential term disappears. Note that microprudential policy will have a positive spillover effect on any macroprudential component: 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.

3.6 A Quantitative Example

We next 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 have the same high exposure to a single systematic factor such that $\rho_i = \rho = .9$. Furthermore, assume that banks stay at the minimum microprudential requirements of 7% (4.5% common equity Tier 1 capital and 2.5% CCB buffer[13]. 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.

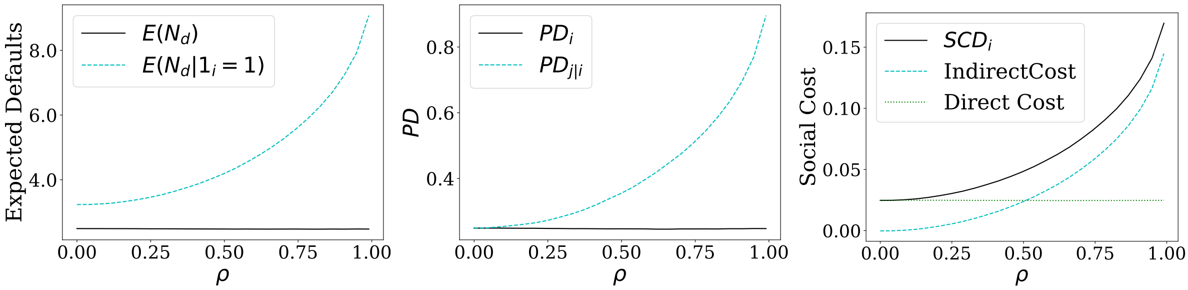
In Figure 2, we vary the banks' exposure to the systematic factor ρ driving the correlation between banks' assets. We can see that as the correlation between banks increases, first the expected number of defaults N_d conditional on bank i defaulting increases, while the average unconditional number of defaults remains unchanged (cf Fig.(4a)): the average number of 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 that the conditional default probability of another bank defaulting given a default in i, $PD_{j|i}$ increases with ρ (cf Fig.(4b)). The direct costs in our SCD function are independent of the correlation, but the Indirect Costs increase from zero when bank defaults are uncorrelated consequently driving up an increase in the total Social Cost of Default (cf Fig.(4c)).

Figure 3 on the other hand shows the effect of increasing the macroprudential capital requirement for bank i while keeping the capital requirement of all other banks at 7%. We can observe several interesting facts. First, while the expected number of defaults decreases slightly since bank i's default probability is reduced, there is an increase in the expected number of defaults and the probability of another default happening conditional on bank i defaulting (cf Fig.(3a) and Fig.(3b)).

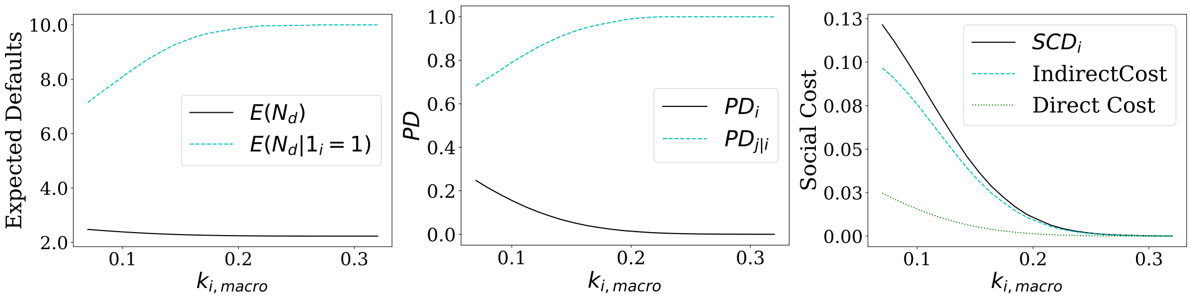
[13] See Annex B for details on the capital requirements.

Figure 2: Asset Correlation



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

Figure 3: Capital Requirements



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

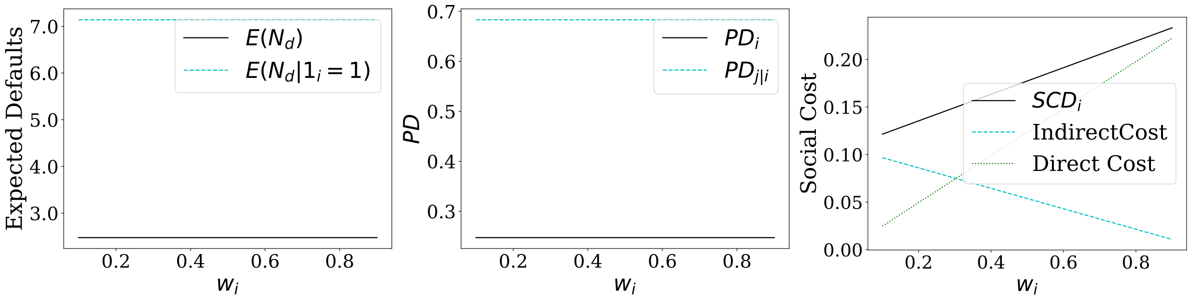
This does not mean that the rest of the system becomes riskier as one might be tempted to conclude at first sight. It simply captures the fact that as the default of bank i gets less likely, observation of it actually taking place nevertheless indicates more severe market distress, which in turn implies 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). Still, 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 (cf Fig.(3c)).

Figure 4 shows the effect of increasing the relative size of bank i while decreasing the size of all other banks proportionally so as to satisfy the adding up requirement $\sum_i w_i = 1$. As w_i increases (and $\sum_{j\neq i} w_j$ decrease correspondingly) we can observe that the direct cost goes up and the indirect costs are reduced (cf Fig.(4c)). This is due to the fact that other affected banks are still similarly affected but they are relatively smaller now. Bank i, on the other hand, becomes relatively larger 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. Relating the observed net results to the definition of SCD in equation (10), the fact that the term $(PD_{j|i} - PD_j)PD_i$ is positive and less than one indicates that as the relative size of bank i increases at the expense of the relative sizes of all other banks its SCD will increase as well.

3.7 Positive Spillovers of Macroprudential Capital

When macroprudential requirements need to be set for a number of key institutions, the policymaker should consider potential positive spillovers between banks. In other

Figure 4: Relative Weight



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

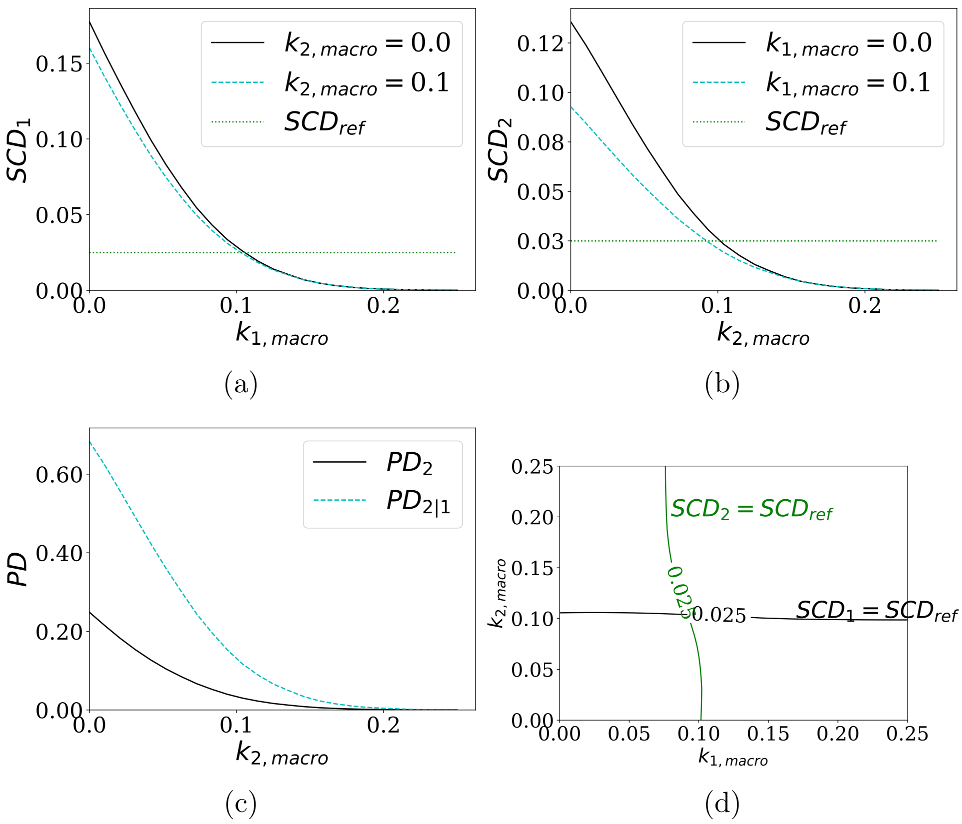
words, increasing the macroprudential capital requirements of one bank lowers the SCD of other banks by reducing their indirect cost of default. This can be seen in equation (10): increasing the capital ratio of banks j, lowers the indirect costs for bank i as long as the $PD_{j|i}$ decreases faster than PD_j.

We illustrate the positive spillovers of capital regulation with a second example. Building up on our previous case, assume again that the financial system consists of ten players, each with the same exposure to the systematic factor of .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 the other banks accounting for the rest are non-systemic and are equally sized. The policymaker sets macro capital buffers again using the EEI approach but now needs to consider the interaction between bank 1 and bank 2's costs of default and determine the optimal capital buffers simultaneously for the two banks. Assume that the reference size of a nonsystemic institution is $w_{ref} = 10\%$.

Figure 5 illustrates the point. 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 can be expected, both its conditional and its unconditional probability of failure is decreasing with higher macroprudential capital allocated to it. Due to the positive correlation between the banks, however, the $PD_{2|1}$ curve is higher than the PD_2 curve as observing a default for bank 1 already increases the chances we will observe a default in 2 as well, due to the positive correlation between the two. 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, indicating that increasing the macroprudential buffer of bank 2 will also tend to lower the SCD of bank 1 as well, as the difference term in (10) will be positive for any $k_{2,macro}$. As a result, increasing the macro capital buffers of bank 2 lowers the SCD of bank 1. This point is illustrated also in Figure 5a, where the $SCD_1(k_{1,macro})$ curve shifts down once $k_{2,macro}$ is increased. A point worth noting is that as the smaller bank (bank 2) becomes safer, as its macro capital buffers increased from 0% to 10%, the spillovers to lower costs of default of the large bank (bank 1) are negligible especially if bank 1 is already well capitalized (Cf Figure 5a). As the larger bank, becomes safer, however, the reduction in SCD for the smaller bank could be significant, as long as that bank is not already significantly capitalized (Cf Figure 5b).

We show in the next section that by setting the optimal macroprudential requirements through an equalization approach, the supervisor has to ensure that the SCD of each systemic bank equals the SCD of a reference non-systemic institution. Figure 5d provides a preview of the lines along which this occurs. The two banks will have a SCD equal to a

Figure 5: Positive Spillovers of Capital Increases



Note. This set of figures shows a quantitative example a financial system consisting of equally-sized banks.

non-systemic institution at the point where the two iso-lines for $(k_{1,micro}, k_{2,micro})$ cross.

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, which is closely related to what is done in practice; and second, a more general explicit optimization-based approach using Acharya et al. (2017)'s Expected Shortfall concept.

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 regulatory framework, is measured through a scoring that ranks institutions by size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity. The overall score, thus, provides rough guidance on the institutions' systemic importance, and a low threshold value can be used as a reference point for the anchor, and the probability-weighted score provides guidance on the expected loss.

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 impact of distress is equalized taking empirically measured default correlations between institutions explicitly into account. We discuss this alternative now.

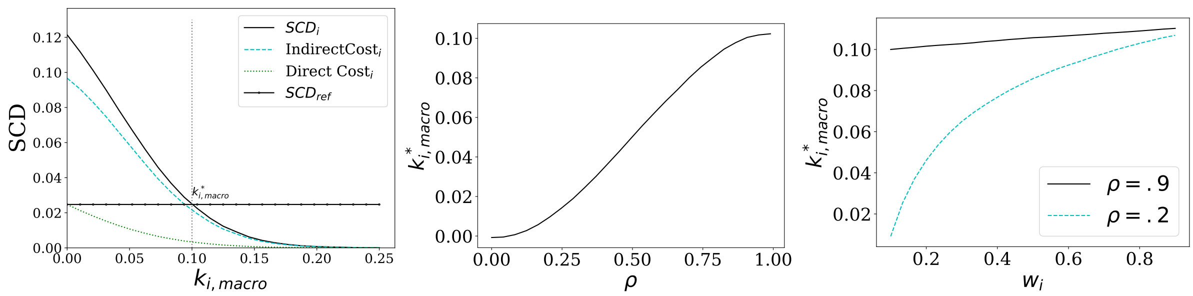
Consider the fact that default probabilities are a function of capital requirements through the default threshold approach established in (4). We can then define the SCD of a benchmark or reference institution which holds micro-prudential capital only and has no indirect cost associated with other institutions as a function of that capital requirement k_{micro}. Still assuming a fixed LGD of 100% we get:

$$SCD_{ref}(k_{micro}, w_{ref}) \equiv w_{ref} PD(k_{micro}) \tag{11}$$

Refer to this bank as the *reference bank*. The next step is to equalize the SCD of an SII bank i presumed to have a systemic social impact to the expected SCD of the reference bank by setting additional capital requirements $k_{i,macro}$ for bank i. Note that the macroprudential capital requirements $k_{i,macro}$ are *additional* buffers that come on top of the stand-alone microprudential buffers $k_{i,micro}$:

$$SCD(k_{micro} + k_{i,macro}, w_i; \rho_i) = SCD_{ref}(k_{micro}, w_{ref}) \tag{12}$$

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 average default correlation between banks and if we vary the size of the bank.

Figure 6a below 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. 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 SII 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 SII 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 that the social costs (both direct and indirect) of the SII bank's distress are decreasing as and 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 (EEI) by raising $k_{i,macro}$ and so lowering the SII bank's SCD to the point where it equals SCD_{ref}. At that point, the default probability of the SII 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 below shows the optimal macroprudential buffer ratio $k^*_{i,macro}$ as a function of each bank's exposure to the systemic factor, captured by ρ. Higher exposure to the systemic factor implies 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 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 for two different values of the correlation parameter ρ. 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 since what happens with one bank is more than likely to happen with the others too at the same time, so the curve is relatively flat. 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

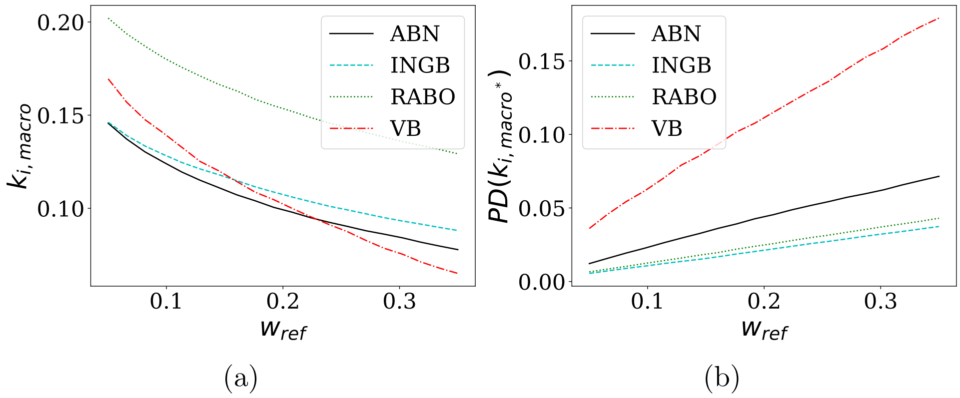
Now, with the theory behind the EEI approach, we look at an empirical application of the model. We apply the EEI approach on a domestic scale to the sub-sample of Dutch banks.[14]

Figure 7 presents the main results. We vary the size of the reference institution. The larger the reference size, the more relaxed the policy constraint to which the systemic bank's SCD needs to be matched. This implies lower overall macro buffers (cf. (7a)) and a tolerance to higher default probabilities (cf. (7b)). As a result, for a smaller bank with a lower overall cost, such as VB, the default probability is allowed to be higher over the range of reference scenarios, while the default probability of a larger bank as INGB is suppressed significantly. Note that the largest macro capital buffers are assigned to RABO. This is the result of the bank being the most sensitive to common shocks with exposure to the main common factor ρ_1 of .95. Furthermore, RABO's implied asset standard deviation is higher than that of the other two large banks, INGB and ABN.

Overall, we find that the EEI buffers are larger than the range within which regulators set the O-SII rates. One needs to note the SCD includes not only the impact of a bank on the system but also the sensitivity of its default to other players defaulting as well.

[14]Cf. Annex A for a description of the dataset.

Figure 7: Optimal Macro Buffers: EEI Approach



Note. This figure shows the implied macroprudential buffers for the Dutch sub-universe. We use $k_{micro} = .07$ which implies $PD_{ref} = 0.33$.

5 The Expected Systemic Shortfall Approach (ESS)

A potential downside of the EEI approach is that it may produce capital buffers that are impractical to enforce. In reality, the policymaker may be constrained by the regulatory framework, or may be concerned that setting capital buffers too high may hurt the lending capacity of systemic banks, thus slowing down economic activity. As a result, we develop an alternative approach again using the modeling the modeling framework of Section 3. In Section 5.2 we apply the ESS approach empirically.

Now the policymaker 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 an average macroprudential target buffer rate against which to allocate. In what follows we first outline the theory then provide an empirical application to our European sample of banks.

5.1 The Expected Systemic Shortfall Approach: Theory

5.1.1 Expected Shortfall and Systemic Risk

Once again the banks in the policymaker's portfolio constitute the financial system. Begin by defining the potential losses for bank i one year from now as a fraction of its outstanding liabilities as

$$L_i = \mathbb{1}_i LGD_i \tag{13}$$

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. At this point, we do not yet make an assumption on the LGDs. They can be random, and possibly correlated across banks, or they can be fixed, in which case the only source of uncertainty is whether default happens or not.

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 weighted by the share w_i of their liabilities in the total liabilities of the sector. In our model of systemic risk, we thus consider the liabilities of individual banks in the sector as the counterpart of the loan portfolio in the securitization literature where this model was initially developed

$$L_{sys} = \sum_{i=1}^{N} w_i L_i \tag{14}$$

We can now relate our framework to a measure of systemic risk developed in Acharya et al. (2017) and Huang et al. (2012). We define the Marginal Expected Shortfall (MES) of a bank as its average loss conditional on total systemic losses being above a threshold $\overline{L}$:

$$MES_i = \mathbb{E}\left(L_i | L_{sys} > \overline{L}\right) \tag{15}$$

We quantify systemic risk as the potential default loss on a portfolio containing all banks in the financial system for which the supervisor is accountable:

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

The additivity property of expectations provides a relationship between total systemic risk and the sensitivity of a bank to the system. We can easily show that

$$ES_{sys} = \sum_{i} w_i MES_i$$

This provides also a useful interpretation of the MES: a bank's weighted MES represents the portion of total systemic risk that can be attributed to it. Lowering the bank's MES by imposing higher capital buffers, thus will lower overall systemic risk.

Figure 8 illustrates the results with the second example considered earlier. Our findings about the SCD in Section 3.5 also apply to the systemic ES and the MES. First, the ES and the weighted MES go up with the increase in the correlation between banks' assets as shown in figure 8a. Second, as Figure 8b shows, bank i's MES goes down with an increase in its capitalization. This pushes down total systemic risk. Third, the positive spillovers from capital increases also hold here (cf. Figure 8c). Overall, Figure 8d shows the combination of bank 1 and bank 2 buffers which can produce the same level of systemic risk.

As a result, the policymaker's problem can be formulated as one of minimizing total systemic risk by choosing the size of the macro buffers for each bank in the system, subject to an average capital ratio:[15]

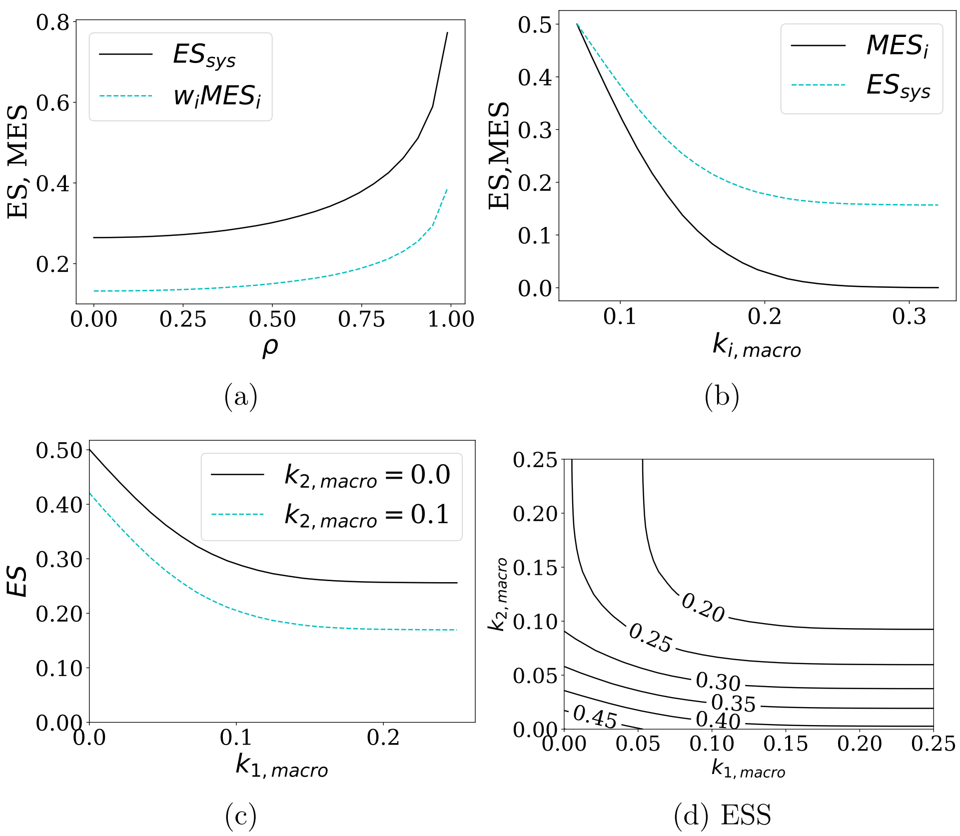
$$\begin{gathered} \min_{k_{1,macro},\dots,k_{N,macro}} ES(k_{micro}; k_{1,macro}, \dots, k_{N,macro}) \\ s.t. \sum_i w_i k_{i,macro} = \overline{k} \end{gathered} \tag{17}$$

[15]Equivalently, this optimization can also be seen as maximizing the net benefit of reduced systemic risk compared to the case with micro-buffers only. In that case, the objective can be written as

$$\begin{gathered} \max_{k_{1,macro},\dots,k_{N,macro}} \{ES(k_{micro}) - ES(k_{micro}; k_{1,macro}, \dots, k_{N,macro})\} \\ s.t. \sum_i w_i k_{i,macro} = \overline{k} \end{gathered}$$

producing essentially the same optimization problem.

Figure 8: Expected Systemic Shortfall



Note. This figure illustrates quantitatively the Expected Shortfall optimization process in a universe with the 10 banks, where bank 1 has 50% liability size and bank 2 has 20% relative liability size, while the rest of the banks in the system are equally-sized.

5.1.2 Determining the optimal $\overline{k}$

The next question that we need to answer following the empirical analysis of the earlier section, is what is the optimal level of *average* macroprudential buffers $\overline{k}$? Policymakers should use this quantity as a target against which to minimize systemic risks in line with the approach established in Section 5.

For this purpose, we look at the policymaker's problem as one of maintaining a healthy supply of credit in the economy. The policymaker thus minimizes an expected costs function comprised of the economic costs of financial distress on one hand and reduced loan supply stock on the other. Higher capital requirements, from that point of view, reduce the probability of a financial crisis, but also bring the risk of inducing banks to reduce lending as a way of satisfying the stricter regulatory constraints. The policymaker needs to balance the two costs for the economy.

Formally, we can write this in to form of an optimization program

$$\min_{\overline{k}} \left\{ P(\overline{k})SCD(\overline{k}) + (1 - P(\overline{k}))SCB(\overline{k}) \right\} \tag{18}$$

where

$$P(\overline{k}) = \mathbb{P}(L_{sys} > \overline{L}), P < 0$$

is the probability that a systemic crisis occurs over the next period, which can be quantified through our banking model so far with the probability of systemic losses exceeding the regulatory tolerance threshold;

$$SCD(\overline{k}) = \lambda \mathbb{E}(L_{sys} | L_{sys} > \overline{L}), SCD' < 0$$

is the economic costs of a financial crisis with λ representing a factor of pass-through from losses in the financial sector to losses for the wider economy expressed as GDP decline.

On the other hand, we define the social cost of imposing higher $\overline{k}$ capital buffers in the cases in which no systemic distress occurs as

$$SCB(\overline{k}), SCB' > 0$$

The optimizing first-order condition then implies that the expected costs of a marginal increase in the macroprudential capital levels need to compensate for the marginal increase in the costs associated with an increase in the aggregate level of the macroprudential buffers

$$P'SCD + PSCD' = P'SCB - (1 - P)SCB'$$

Given a macroeconomic production function, we quantify SCB through the reaction of aggregate output to an increase in capital requirements via reduced credit lending in the economy. The SCB can be seen as cost in terms of reduced aggregate output 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.Cf. Jakucionyte and van Wijnbergen (2018) for discussion on the macro effects of higher capitalization of the banking system with risk-shifting and debt overhang problems. Our goal is thus, without specifying a full-blown macro model, to quantify this reaction as the relative rate of change term:

$$\eta = -\frac{dY/d\overline{k}}{Y} = -\left(\frac{dY}{dC}\frac{C}{Y}\right)\left(\frac{dC}{d\overline{k}}\frac{1}{C}\right) \tag{19}$$

where C is the total equilibrium level of credit in the economy. η will then represent the percentage drop in GDP for a one percentage point increase in the macroprudential ratio requirement.[16]

Then we can write

$$SCB(\overline{k}) = \eta \left(\overline{k} - \overline{k}_0\right) \tag{22}$$

with $\overline{k}_0$ the initial level of macroprudential capital buffers.

Next, we focus on the empirical implementation of the model for a universe of European banks.

5.2 The Expected Systemic Shortfall Approach: Empirics

Next, we apply a minimum risk approach to the calibration of systemic buffers, targeting the current average level of O-SII buffer rates set by the regulator. We want to verify whether, given the current risk tolerance of the regulators that speaks from the current average O-SII rates, the risk buffers can be allocated more efficiently.

Figure 9 shows the model-based macroprudential rate if they were set on a European scale compared to the current national O-SII rates. The last column shows the difference between our model-based estimate and the O-SII rate set by the regulator. It can be seen that the optimization model prefers to allocate higher buffers consistently to the universe of French and to some extent Dutch banks, while it compensates by allocating lower buffers to the Netherlands and Germany. Naturally, this does not immediately imply that certain Europan jurisdictions are allocating the buffers inefficiently. The discrepancy largely is a result of the objective underlying the O-SII framework in which regulators measure the impact of local banks on the local economy only, relative to the size only of other local players.

Table (1) shows the same analysis when Dutch banks' capital buffers are set to the Dutch average. Within a domestic scale, which is in fact the intended implementation of the O-SII framework, it can be seen that the allocation of optimal buffers do not differ significantly from the O-SII rates. As illustrate earlier, the discrepancy between model recommendations and actual O-SII rates is much more noticeable between countries than within countries.

Figure 10 further shows the results on the four Dutch systemic banks when we vary the constraint on the average buffer. We can see observe that optimal Macroprudential

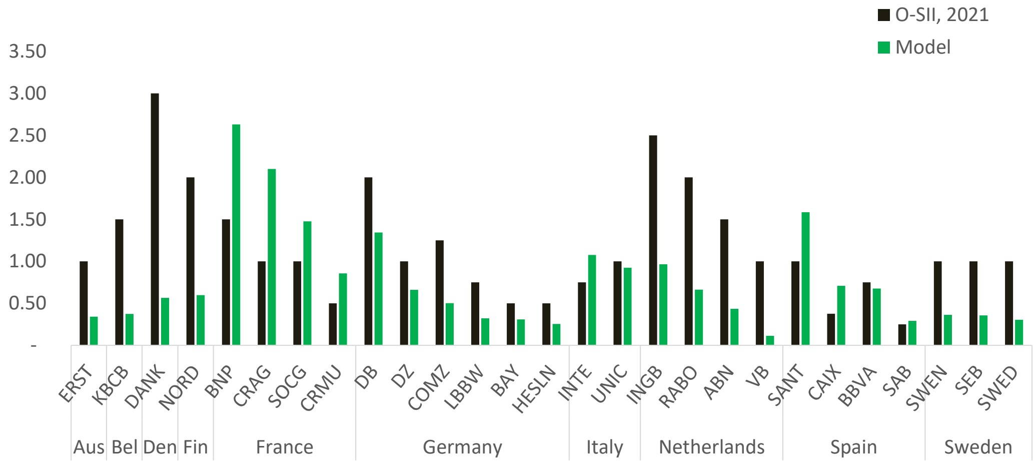
[16]The literature on the long-term impact of capital buffers looks at an alternative approach where the increase in capital buffers raises the cost of lending, and as a result the cost of capital. Miles et al. (2013) for example define the cost of capital increase through the effect a rise in the cost of capital has on GDP via an aggregate production function with constant elasticity of substitution in a standard macro model as

$$\frac{dY}{dP_K}\frac{P_K}{Y} = \left(\frac{dY}{dK}\frac{K}{Y}\right)\left(\frac{dK}{dP}\frac{P}{K}\right)\left(\frac{dP}{dP_K}\frac{P_K}{P}\right) \tag{20}$$

$$= \alpha\sigma\frac{1}{1-\alpha} \tag{21}$$

where α is the elasticity of output w.r.t. capital, and σ is the elasticity of substitution between capital and labour. As a result, 1% increase in the cost of capital leads to $\alpha\sigma\frac{1}{1-\alpha}$% drop in aggregate output. Mapping quantitatively the increase in the capital ratio to an increase in the overall lending costs is a matter of quantifying a deviation from the Modigliani-Miller propositions which would make equity financing more costly for the bank compared to debt financing.

Figure 9: Optimal Macro Buffers at current O-SII average



Note. This figure shows the 2021 O-SII required rates against the capital requirements based on minimizing the systemic ES. The system is set to represent the major European banks from our universe. The model-based capital buffers are evaluated against the average O-SII rate in the universe of 1.25%.

Table 1: O-SII Buffers, ES Approach for Dutch SIIs (%)

Bank	O-SII Rate	$k^*_{i,macro}(\overline{k}_{osii})$	$k_{i,macro}(\overline{k} = 3\%)$
ABN	1.50	1.41	2.01
INGB	2.50	2.61	3.73
RABO	2.00	1.92	2.75
VB	1.00	0.67	0.96

Note. This table shows the actual O-SII macroprudential buffer rates (as of 2021) vs. the model-based rates evaluated at the current weighted average of 2.1% and at an average of 3%.

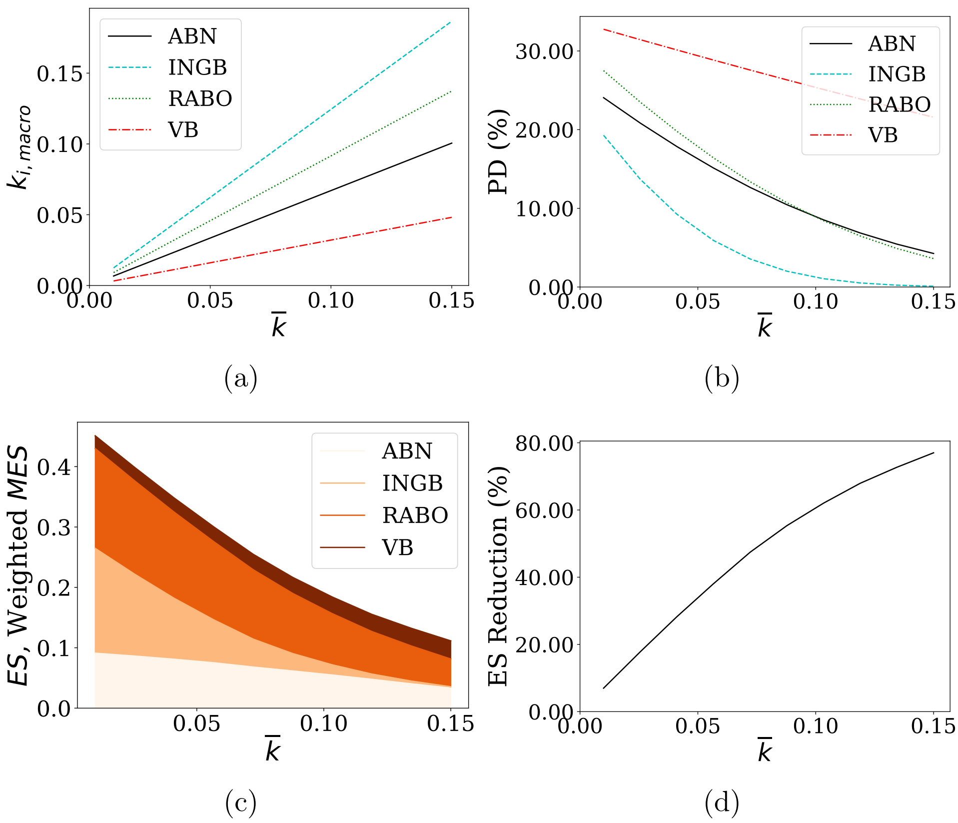
requirements increase linearly with the relaxation of the constraint, while the default probabilities decrease nonlinearly. Total systemic risk, quantified through the ES of the system decreases. The contributions of INGB, RABO, and ABN to overall risk. expressed by the weighted MES, decreases. Figure 10 finally shows the percentage reduction in ESS relative to the case where only microprudential buffers are set.

5.3 Calibration for the Optimal $\overline{k}$

Next, we turn to parametrizing the optimization problem (18). The core assumption behind our approach is that increased capitalization requirements will lead to a negative lending shock. However, we refrain from making explicit assumptions about the channel through which lending is reduced. It is outside of the scope of this paper to create a full banking model. Also, we refrain from the approach used in part of the literature of quantifying Modigliani-Miller deviations and of estimating the pass-through of higher financing costs to the public.Cf. Cline (2017) for an extensive discussion of this approach. Empirically, the two questions have been a matter of debate (Cf. 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

Figure 10: Minimizing Systemic ES, Dutch Sub-sample



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.

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 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.

On quantifying the impact of reduced credit supply to lower GDP growth, we rely on Barauskaitė et al. (2022), who in a BVAR framework with sign and inequality restrictions, determine that a 1% reduction in loan supply would result in a worst-case scenario of about .6% reduction in GDP growth.Refer in particular to Figure 3 in Barauskaitė et al. (2022) outlining the impulse-response functions from a credit supply shock. Overall, we then get a baseline figure for η of .024.

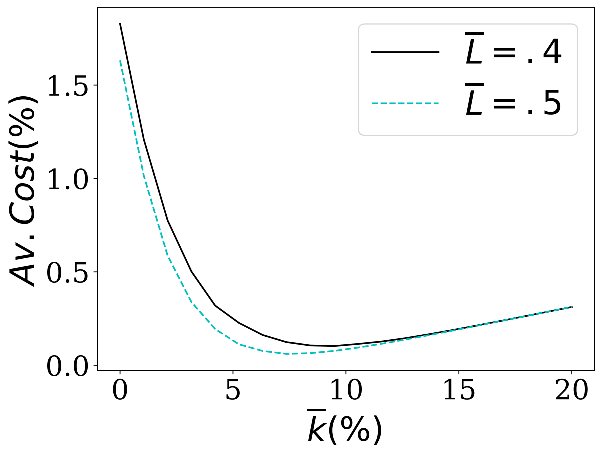
Finally, to calibrate the λ parameter in our model, we need to reconcile our assumption of the LGDs of banks with the potential of a banking crisis to spill over to the real economy. For this purpose, we refer to Reinhart and Rogoff (2009) who find that on average a banking crisis associated with a recession produces a 9% decline in GDP from peak to through. We have assumed, somewhat arbitrarily an LGD figure of 100%. Assuming that a banking crisis occurs if one-half of the financial institutions are set to default without government intervention, this would indicate systemic losses of 50%. The λ then captures the ratio of those losses and the loss for the real economy. As a crude baseline figure, then we use the ratio of GDP losses to financial losses in our model, such that $\lambda = \frac{9\%}{.5 \cdot 100\%}$. Table 2 summarizes the parameter choice values.

Table 2: Model Input Data

Variable	Value	Source
η	.024	
$(dY/dC)(C/Y)$	.006	Barauskaitė et al. (2022)
$(dC)(d\overline{k})(1/C)$	-.04	Favara et al. (2021)
λ	.18	Implied from Reinhart and Rogoff (2009)

Note. This table shows the parameter values for the policymaker social optimization problem.

Figure 11: Macroprudential Cost Function

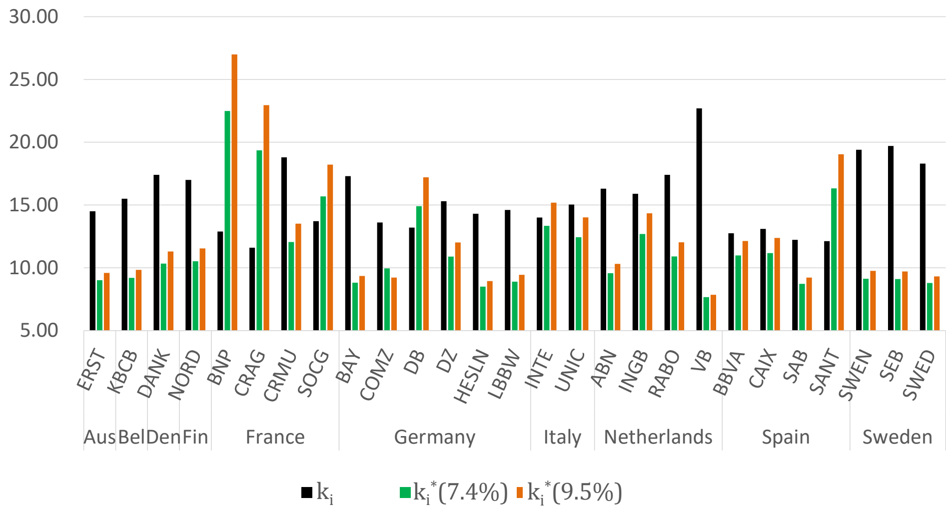


Note. This figure shows the policymaker's macroprudential cost function in terms of expected output loss.

Figure 11 illustrates the results, showing the range of the estimated output costs for the baseline parametrization of the model. The parameter $\overline{L}$ governs the policymaker's tolerance to systemic losses, indicating the aggregate losses, relative to the outstanding liabilities, above which one can judge that a systemic financial crisis is present. A higher level of $\overline{L}$ indicates that the policymaker is willing to tolerate smaller losses before stepping in.

Clearly, the less risk-averse the policymaker is, the lower the average macro buffers are set. The figure illustrates two cases, with $\overline{L} = .4$ and $\overline{L} = .5$. The minimizing condition indicates an average macro-buffers $\overline{k}$ of 9.5% in the first case, and of 7.4% in the second, with an expected output cost at the minimum point accounting for .1% in the first case and .06% in the second.

Figure 12: Overall Capitalization (%)



Note. This figure shows the current CET1 capitalization ratios (k_i) vs. the model-based total capital requirements (micro plus macro, k_i^*) at 7.4% and at 9.5% capital buffer.

Figure 12 shows the distribution of the total capital buffers from the model across the banks in our sample. In this context, we prefer to compare the model outcomes to the total CET1 capitalization in order to capture also the fact that banks may be subject to additional buffer requirements that were not discussed so far, such as the CCyB and the SyRB[17]. Our approach highlights areas where the banks are undercapitalized relative to the model recommendation, especially in France, Italy, and Spain.

6 Conclusions

In this paper, we address the problem of calibrating the macroprudential capital buffers of banks by developing 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 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 in practice by regulators to determine systemic buffers in the O-SII and G-SII frameworks. The equalization approach is widely used in practice 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 see 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

[17] Cf. Annex B for details on these policy frameworks.

advantage in that it allows us to integrate into the analysis also 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 constructed a solution assuming a hypothetical single European regulator setting socially optimal buffers across banks.

Finally, employing a cost and benefit analysis, we showed that the average size of the macroprudential buffers can be calibrated to a social optimum. Thus, we relate to the discussion of macroprudential capital buffers to an earlier discussion on the economic cost of capital (BCBS, 2010). We find that a cross-sectional average of 7.4% to 9.5% macroprudential add-on CET1 requirement rate (on top of the microprudential requirements of 4.5% minimum plus the 2.5% CCB) 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. 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 possible extensions that future research can address. First, the currently proposed portfolio approach could be extended to incorporate specific core-periphery features of the financial network in Europe.[18] The addition of a network structure, from that point of view, 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.

Further, 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 also focus on introducing 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 modeling basis that can be used as a stepping stone for further discussions on the macroprudential frameworks and on the calibration of the size of banks' capital buffers.

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

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A Data

We use data from 27 European banks. The dataset includes weekly prices on the CDS spreads on subordinate debt provided by Bloomberg, and annual end-of-year balance sheet liability size figures and current CET1 capitalization ratios, provided by FactSet. A three-factor latent model is then estimated based on weekly CDS data in the period August 2019 to August 2022. 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.

Throughout, we use an LGD assumption of 100%. 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 or the ES buffers, as it is assumed to be the same for all banks.

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 3 summarizes the input data and the implied model parameters.

Table 3: Model Input Data

Country	Code	Name	w_{euro}	w_c	CDS (bps)	$PD(\%)$	ρ_1	ρ_2	ρ_3	$\hat{\sigma}(\%)$	k_{CET1}
Austria	ERST	Erste Group	1.51	100.00	79.80	0.78	0.69	(0.22)	0.17	6.60	14.50
Belgium	KBCB	KBC	1.67	100.00	214.03	2.03	0.17	(0.15)	0.11	8.30	15.50
Denmark	DANK	Danske Bank	2.66	100.00	266.43	2.50	0.96	(0.06)	(0.14)	9.76	17.40
Finland	NORD	Nordea	2.82	100.00	131.16	1.27	0.59	0.71	(0.20)	8.40	17.00
France	BNP	BNP Paribas	13.24	37.59	163.10	1.57	0.96	(0.17)	(0.10)	6.54	12.89
France	CRAG	Credit Agricole	10.51	29.85	156.92	1.51	0.95	(0.19)	(0.12)	5.84	11.60
France	SOCG	Societe Generale	7.32	20.78	206.83	1.97	0.51	(0.09)	0.04	10.10	18.80
France	CRMU	Credit Mutuel	4.15	11.79	192.76	1.84	0.93	(0.15)	(0.10)	7.18	13.71
Germany	DB	Deutsche Bank	6.64	41.68	64.24	0.63	0.33	0.02	0.27	7.70	17.30
Germany	DZ	DZ Bank	3.14	19.74	317.91	2.95	0.96	(0.14)	(0.03)	7.84	13.60
Germany	COMZ	Commerzbank	2.33	14.61	328.06	3.03	0.93	(0.11)	0.04	7.66	13.20
Germany	LBBW	LBBW	1.41	8.84	49.95	0.49	0.26	(0.12)	(0.04)	6.55	15.30
Germany	BAY	Bayern LB	1.34	8.43	69.33	0.68	0.37	(0.01)	0.12	6.38	14.30
Germany	HESLN	Helaba	1.07	6.70	51.96	0.51	0.40	(0.14)	0.03	6.27	14.60
Italy	INTE	Intesa Sanpaolo	5.28	54.04	323.84	3.00	0.92	(0.09)	(0.12)	8.11	14.00
Italy	UNIC	Unicredit	4.49	45.96	362.50	3.32	0.92	(0.08)	(0.09)	8.93	15.03
Netherlands	INGB	ING	4.71	46.22	104.46	1.02	0.73	(0.00)	0.27	7.76	16.30
Netherlands	RABO	Rabobank	3.15	30.94	70.71	0.69	0.73	0.10	(0.14)	7.13	15.89
Netherlands	ABN	ABN Amro	1.99	19.54	157.35	1.51	0.95	(0.12)	(0.11)	8.87	17.40
Netherlands	VB	Volksbank	0.34	3.30	95.29	0.93	0.67	(0.10)	0.19	10.90	22.70
Spain	SANT	Santander	7.87	50.03	230.76	2.18	0.95	(0.13)	(0.02)	6.89	12.75
Spain	CAIX	Caixabank	3.38	21.51	225.64	2.14	0.20	0.07	0.49	7.05	13.10
Spain	BBVA	BBVA	3.22	20.49	365.34	3.35	0.31	0.09	0.61	7.24	12.22
Spain	SAB	Sabadell	1.25	7.97	214.60	2.04	0.96	(0.12)	(0.04)	6.46	12.12
Sweden	SWEN	Handelsbanken	1.61	35.70	133.98	1.30	0.67	0.65	(0.06)	9.70	19.40
Sweden	SEB	SEB	1.59	35.09	139.54	1.35	0.62	0.72	(0.03)	9.92	19.70
Sweden	SWED	Swedbank	1.32	29.20	164.63	1.58	0.66	0.37	0.24	9.43	18.30

Note. This table shows the CDS spreads on the Dutch sub-sample, size, capitalization, implied PD, st. dev. of assets and the estimated factor model loadings. The two columns w_{euro} and w_c show the liability size of the institutions on a European and on a domestic scale, repsectively.

B Regulatory Capital Requirements in the Netherlands

Short overview of the different regulatory capital requirements[19]

1. Minimum Capital Requirement (Basel III) must be maintained at all times:
    - 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 (CET1/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.
2. 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.
3. Countercyclical 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 RWAs.
4. Systemic risk buffer (SyBR)
    - Additive to other buffers. Designed to address risk spillover from the economy (from the system) to individual banks.
    - Purely at the discretion of national authorities based on expert judgment.
    - 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.).
5. Global Systemically Important Institution (G-SII) buffers on Globally Systemically Important Banks (G-SIBs): Add-on to SyBR. 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.
6. Other Systemically Important Institution (O-SII) buffers

[19] 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.

- Add-on to SyBR. 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.

C 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

$$DD_{i,t} = -\Phi^{-1}(PD_{i,t}) \tag{23}$$

Observed changes in the default probability can then be linked to the changes in the asset value by first-differencing (23) and relating it to (4):

$$\Delta\Phi^{-1}(-PD_{i,t}) = \Delta DD_{i,t} = \frac{\ln V_{i,t} - \ln V_{i,t-1}}{\sigma_i\sqrt{T-t}} \tag{24}$$

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

$$\mathbb{Corr}(U_{i,t}, U_{j,t}) = \mathbb{Corr}(\Delta DD_{i,t}, \Delta DD_{j,t}) \equiv a_{i,j} \tag{25}$$

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

$$\Sigma \equiv \begin{bmatrix} 1 & a_{12} & a_{13} & \dots & a_{1N} \\ a_{21} & 1 & a_{23} & \dots & a_{2N} \\ \dots & \dots & \dots & \dots & \dots \\ a_{N1} & x_{N2} & x_{N3} & \dots & 1 \end{bmatrix} \tag{26}$$

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:

$$\min_{\rho_i,\dots,\rho_j} \sum_{i=2}^{N} \sum_{j=1}^{N} (a_{ij} - \rho_i \rho_j')^2 \tag{27}$$

D 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.[20]

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:

$$\underbrace{CDS_t \int_t^{T_{cds}} e^{-r_\tau \tau} \Gamma_\tau d\tau}_{\text{PV of CDS premia}} = \underbrace{(1 - ERR_t) \int_t^{T_{cds}} e^{-r_\tau \tau} q_\tau d\tau}_{\text{PV of protection payment}} \tag{28}$$

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 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 probability q at time t follows from equation (28):

$$q_t = \frac{aCDS_t}{a(1 - ERR_t) + bCDS_t} \tag{29}$$

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.

[20]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.