TI 2023-002/IV
Tinbergen Institute Discussion Paper

Macroprudential Regulation: A Risk Management Approach

Sweder van Wijnbergen[1]
Daniël Dimitrov[1]

1 University of Amsterdam and Tinbergen Institute

Tinbergen Institute is the graduate school and research institute in economics of Erasmus University Rotterdam, the University of Amsterdam and Vrije Universiteit Amsterdam.

Contact: discussionpapers@tinbergen.nl

More TI discussion papers can be downloaded at https://www.tinbergen.nl

Tinbergen Institute has two locations:

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

Macroprudential Regulation: A Risk Management Approach*

Daniel Dimitrov† D.K.dimitrov@uva.nl

Sweder van Wijnbergen‡ S.J.G.vanwijnbergen@uva.nl

January 18, 2023

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 balancing the social costs and benefits of higher capital requirements. The model is applied to the European banking sector.

JEL codes: G01, G20, G18, G38

Keywords: systemic risk, regulation, implied market measures, financial institutions, CDS rates

*We thank Kenny Martens, Thomas van den Berg, Saskia de Vries, Jeroen Huiting, Maurice Bun and Paolo Bonomolo (all from DNB); Franc Klaassen (UvA); Fabian Greimel (UvA); Dimitris Mokas (EBA); David Martinez-Miera (Universidad Carlos III) and seminar participants at the UvA and at DNB for many helpful comments and discussions. We are thankful to Meilina Hoogland (DNB) for the data updates. We acknowledge financial support from De Nederlandsche Bank. All views expressed here are those of the authors and are not necessarily supported by the DNB.

†University of Amsterdam, Tinbergen Institute.

‡University of Amsterdam, CEPR and Tinbergen Institute.

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 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]

Central Banks rely on a list of assigned regulatory score-based measures of systemic impact, in line with EBA guidelines targeting the identification of globally and domestically important banks (G-SIBs and D-SIBs, respectively). Broadly speaking, banks are ranked according to a number of indicators such as size, interconnectedness with the rest of the financial system, substitutability/importance in the lending market, complexity, and cross-border activity. Based on their overall weighted ranking score, regulators allocate banks 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 within the Eurozone. For want of a generally accepted basic framework, aligning these diverging approaches has proven to be difficult.[3]

On the academic front, 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. In this paper we answer precisely that question, following up on the credit risk approaches employed in Dimitrov and van Wijnbergen (2023) for measuring the major contributors to systemic risk in a sample.

There is extensive academic literature on macroprudential policy, but its focus is almost exclusively on interventions aimed at limiting household leverage in the mortgage

[1] Cf. ESRB (2021).

[2] Cf. EBA (2020); ESRB (2017). Apart from the fact that the O-SII framework aims to capture spillover effects to the domestic economy and the G-SIB frameworks to the global economy, a number of nuances exist between the two regulatory regimes that we do not discuss here.

[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.

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.

We use 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 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, building on Dimitrov and van Wijnbergen (2023), 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 make banks safer by forcing them to deleverage.

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 builds 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. 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.

To that end, we develop a novel bank-specific measure of systemic importance based on

[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.

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 lowers its own expected default costs, and at the same time lowers the component of its social costs associated with other banks 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 the application of the EEI approach to be fully based on information embedded in market prices.

In what follows, however, we also demonstrate 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. In order to overcome this shortcoming, we also develop an alternative to the EEI, by formulating 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 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 is related to 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

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

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]

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 modeling (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 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 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

[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.

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 5.3, 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.

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 - 3.3, we consider banks' default risk in isolation; but in Section 3.4 we lay the foundation of our approach, defining what drives distress correlations and how CDS data can be used to obtain the relevant empirical estimates. In Section 3.5 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 3.6.

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 governs the risks to a bank's creditworthiness over the coming one-year period. U_i is not directly observable by depositors or the regulator, not even when U_i crosses a critical threshold, on which more below. A higher realization of U_i indicates a better state of nature and consequently a lower default probability over the coming one-year period.[7][8]

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 basic structure of the Merton model that we utilize to capture the credit risk of an individual bank.

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

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

[7] The model can easily be generalized to incorporate a non-Gaussian 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 richer parametric model than the normal distribution becomes difficult to justify. For this reason, we continue here with the standard Gaussian framework. Note however that even if the default of individual banks is governed by a Gaussian factor, the aggregated losses generated for the system will not be.

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

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

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

Consider next the well-known[9] 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:

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

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.[10] 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:

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

[9] Cf. for example, Lando (2004) for clarifications and details on this.

[10] 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.[11][12]

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) 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.

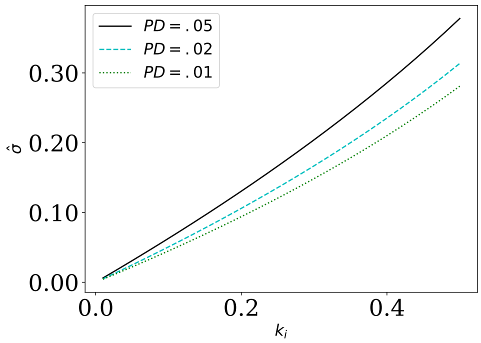
Table 3 in the Annex shows the implied asset standard deviations for the European sample of banks used in the consequent empirical analysis.

[11] Annex D provides the details behind this CDS pricing formula.

[12] 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.

[12] 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 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.

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:

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

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), which are bank-specific (see Annex (B)).

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.[13] 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 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.

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

3.4 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 (cf. 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.[14] 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 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 Appendix C 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 3 in Annex A shows the fitted model exposures for 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 of a bank. The measure encompasses the expected losses in case of default of the bank as a special case, 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

[14] 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.

- 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.

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.[15] Then, we can write the suggested systemic loss function as:

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

The expression above illustrates clearly how microprudential regulation directly targets the own default for bank i, while macro-prudential regulation 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. If bank defaults are uncorrelated we have that $PD_{j|i} = PD_j$, and the macro-prudential term disappears from Equation 10. Also, Equation 10 shows 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

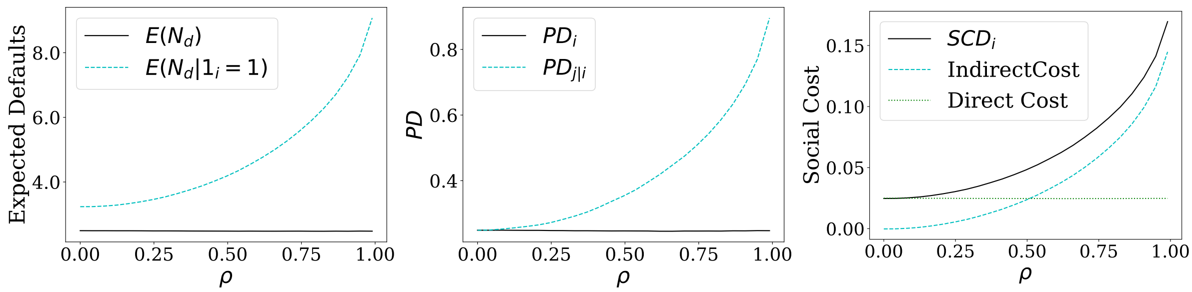
Before turning to the empirical application in Sections 4 and 5 we illustrate some implications of the model using a quantitative example. Assume for simplicity that there are ten equally-sized banks and that all their liabilities are lost in case of default, i.e. $w_i = 1/10$ and with $LGD_i = 100\%$. Assume further that in the base case all banks have the same high exposure to a single systematic factor such that $\rho_i = \rho = .9$. Also, assume that banks stay at the minimum microprudential requirements of 7%.[16] 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

[15] In the credit risk space, w_i corresponds to the Exposure at Default (EAD) of the bank.

[16] 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.

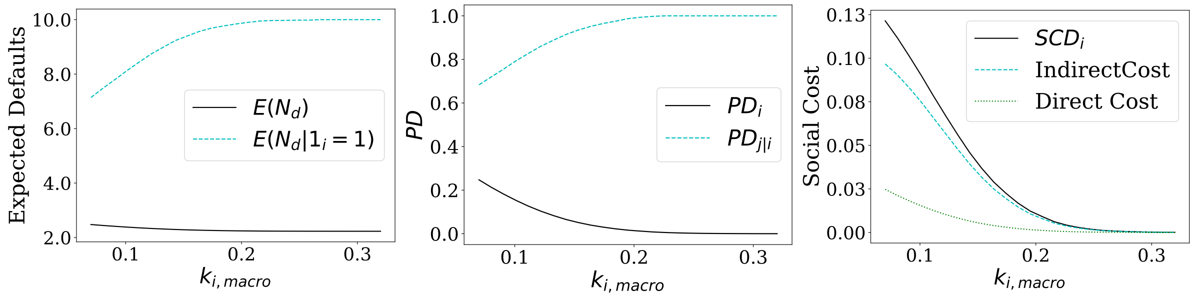
increases, the expected number of defaults conditional on bank i's default ($\mathbb{E}(N_d|\mathbb{1}_i = 1)$) increases, while the average unconditional number of defaults ($\mathbb{E}(N_d)$) remains unchanged (cf. Fig. 2a): the average number of (unconditional) defaults is unrelated to the degree 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 Social Costs of Default are shown in Figure 2c: the direct Social Costs of Default (the first term in the RHS of equation 10) are independent of the correlation. But the indirect costs (the second term in the RHS of equation 10) are zero for zero correlation but rise with increasing ρ. Obviously, the total costs of default (the sum of direct and indirect costs) equal the direct costs for zero ρ but increase with higher ρ in line with the indirect costs (cf Fig. 2c).

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. 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 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 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.

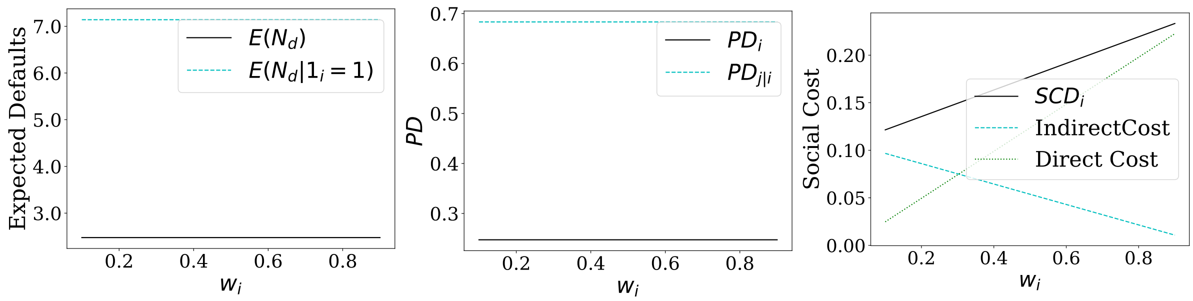
Figure 3: Capital Requirements



(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.

Figure 4: Relative Weight



(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.

3c).

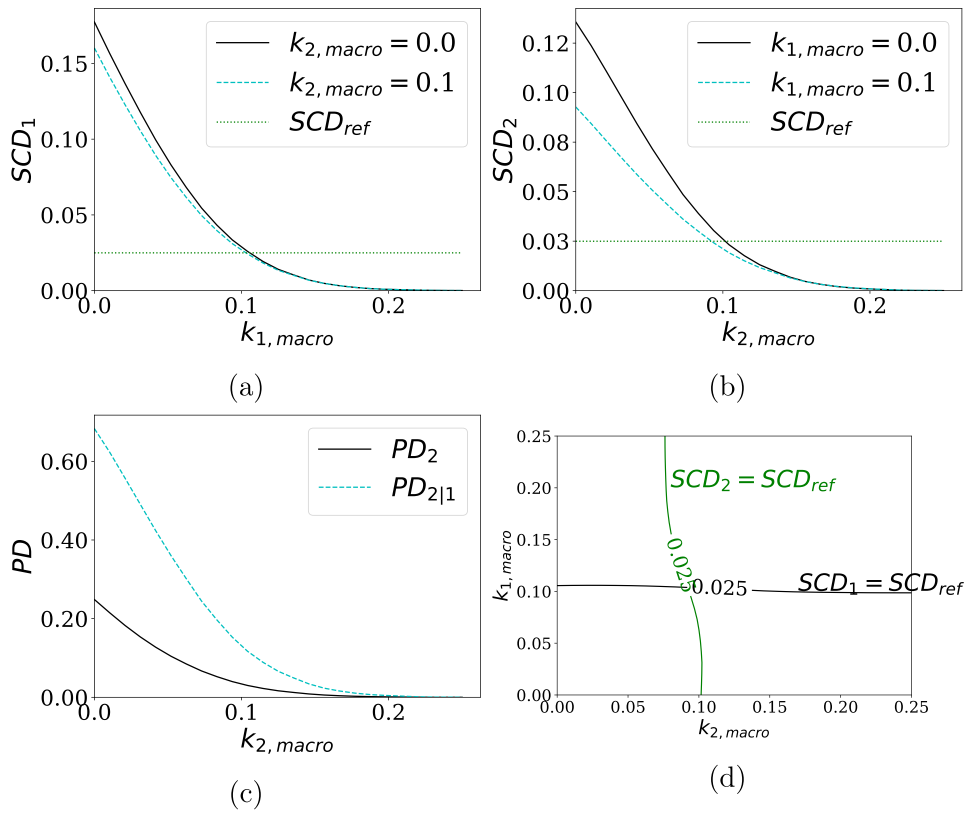
Finally, Figure 4 shows the effect of increasing the relative size of bank i while decreasing the relative size of all other banks proportionally so as to satisfy the adding up requirement $\sum_i w_i = 1$. The impact is not trivial: as w_i increases (and $\sum_{j \neq i} w_j$ decreases correspondingly), 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 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 (10): 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.

3.7 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 (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 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 Capital Increases



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 (10) 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. In this approach, widely used in practice, 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.

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 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. Still assuming a fixed LGD of 100% we get:

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

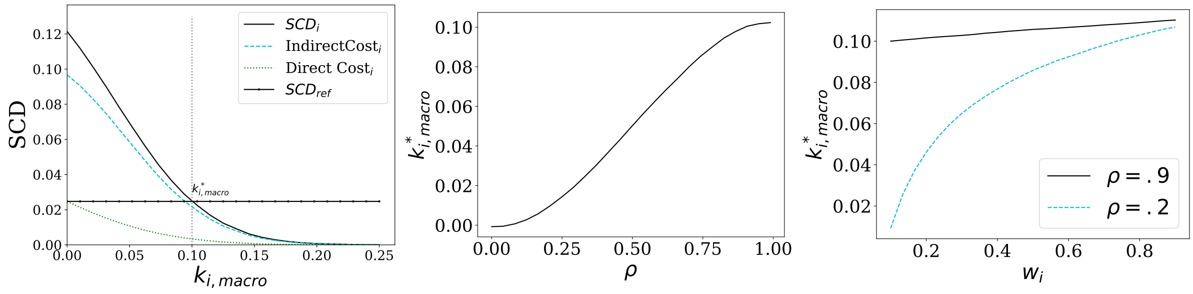
Refer to this bank as the *reference bank*. The next step is to equalize the SCD of bank i presumed to have a systemic relevance to the expected SCD of the reference bank. This is done by requiring the systemic bank to raise its capital ratio by $k_{i,macro}$. In that sense, the macroprudential capital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

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

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 3.6. 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.

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.

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.

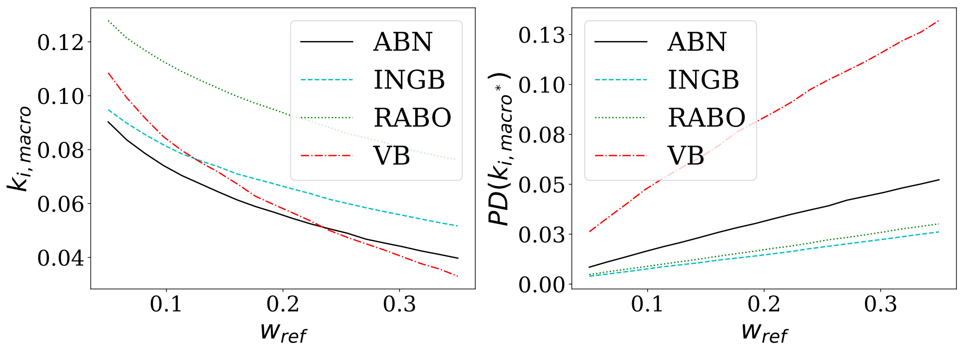
4.2 Systemic Risk and the EEI framework: Empirics

Now, with the theory behind the EEI approach worked out, we present an empirical application of the model. We apply the EEI approach on a domestic scale to the subsample of Dutch banks.[17]

Figure 7 presents the main results. In the figure, we show the impact of varying w_{ref}, the size of the reference institution, on the EEI buffers for the main four Dutch banks in our sample. As we saw earlier, the smaller the assumed reference size, the more conservative the policymaker is in setting the macro buffers. This implies higher overall macro buffers as shown in Figure 7a, and as a result, lower tolerance for bank default, which lowers PDs in Figure 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 current buffers have been set. Part of that difference is due to the fact that the SCD includes not only the direct impact of a bank on the system but also the sensitivity of its default to other players defaulting as well.

Figure 7: Optimal Macro Buffers: EEI Approach



(a) (b)

Note. This figure shows (a) the implied macroprudential buffers for the Dutch sub-universe, and (b) the corresponding probability of default. For the individual banks, we use a micro buffer of 7% (4.5% minimum requirement and 2.5% CCB) plus the corresponding bank-specific P2R rate (1.13% for ABN; 0.98% for INGB; 1.07% for RABO; and 1.69% for VB. For the reference institution we use 8% micro buffer). For the reference institution we use $k_{ref,micro} = .08$.

5 The Expected Systemic Shortfall Approach

One potential downside of the EEI approach is that it may produce capital buffers that are impractical to enforce. And its dependence on an arbitrarily chosen and sized anchor may also be considered a shortcoming. Finally, in real-world circumstances, the policymaker may be concerned that setting capital buffers too high may hurt the lending capacity of systemic banks, thus slowing down economic activity. We develop an alternative approach taking such factors into account, again using the modeling framework of Section 3. In Section 5.1 we first work out the theory of what we labeled the ESS approach. And in Section 5.2 we apply the ESS approach empirically to our European sample of banks. We

[17] Refer to Annex A for a description of the dataset.

do this in two steps. 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. We want to verify whether the risk buffers can be allocated more efficiently, given the current risk tolerance of the regulators about which speaks the current average O-SII rates.

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 an average macroprudential target buffer rate and then allocates buffers to individual systemic banks such that these average out to the macroprudential target buffer size.[18]

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. Later on, we will assume that the LGDs are known and fixed, in which case the only source of uncertainty is whether default happens or not. In general, however, the same setting outlined here can be used even if they are modelled as random, and possibly correlated processes across banks.[19]

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 $\overline{L}$:

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

[18] This allocation procedure is similar to the way Acharya et al. (2017) allocate macroprudential tax rates subject to an average target tax rate.

[19] Cf. Dimitrov and van Wijnbergen (2023) for an application of this approach.

We 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:

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

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. Fig.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, and writing the ES of the system as a function of all banks' capital ratios, the policymaker's problem can be formulated as one of minimizing total systemic ES by choosing the size of the macro buffers for each bank in the system simultaneously

$$\begin{aligned} &\min_{\boldsymbol{k}_{macro}} ES_{sys}(\boldsymbol{k}_{micro} + \boldsymbol{k}_{macro}) \\ &s.t. \quad \boldsymbol{w} \cdot \boldsymbol{k}_{macro} = \overline{k} \end{aligned} \tag{17}$$

where $\boldsymbol{k}_{macro}$ and $\boldsymbol{k}_{micro}$ are column vectors holding all bank-specific micro- and macro-prudential capital ratios, $\boldsymbol{w}$ is a vector of bank sizes, and $\overline{k}$ is a target weighted average macro add-on ratio.[20]

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.

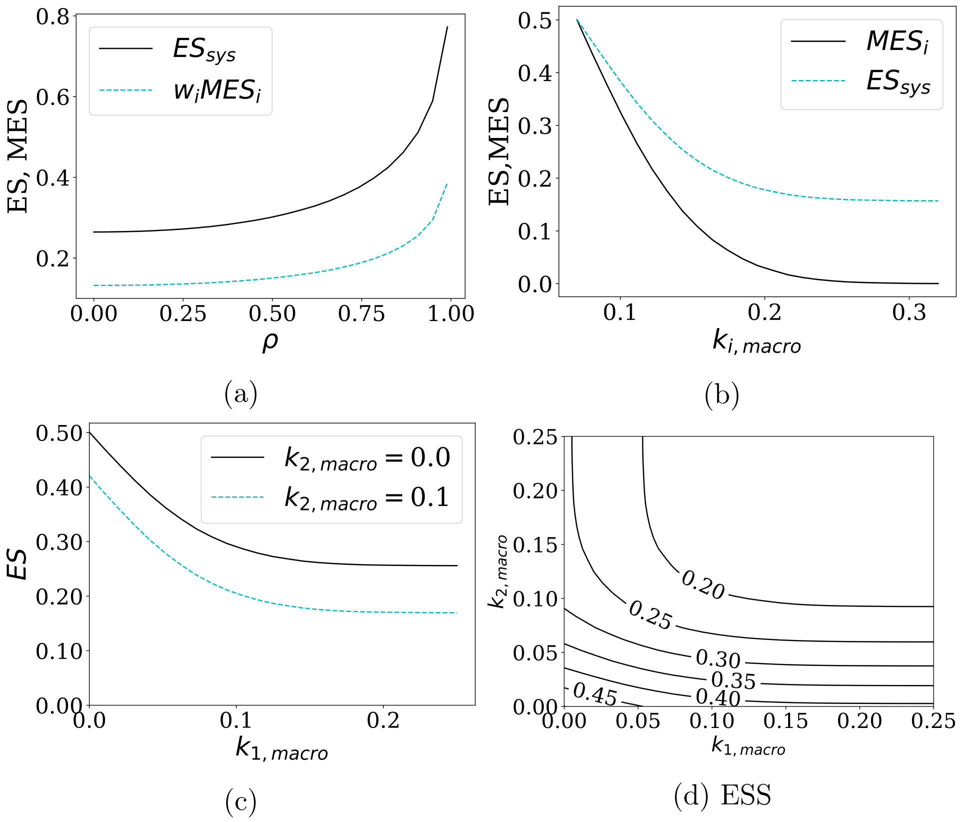
For this purpose, we look at the policymaker's problem as one of maintaining a healthy supply of credit in the economy while managing the risk of a systemic crisis from materializing. The policymaker thus minimizes an expected costs function comprised of the economic costs of financial distress on one hand and reduced loan supply stock on the

[20]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

$$\begin{aligned} &\max_{\boldsymbol{k}_{macro}} \{ES_{sys}(\boldsymbol{k}_{micro}) - ES_{sys}(\boldsymbol{k}_{micro} + \boldsymbol{k}_{macro})\} \\ &s.t. \quad \boldsymbol{w} \cdot \boldsymbol{k}_{macro} = \overline{k} \end{aligned}$$

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 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.

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.

Through the framework established earlier we can relate the probability that a systemic crisis occurs to the average capital requirements. In the context of our model of banking distress as losses in a credit portfolio, we define $P(\overline{k})$ as the probability that total default losses in the system over the coming year will exceed the regulatory tolerance threshold

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

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

Note that $\overline{L}$ determines the intervention threshold for the regulator, and implicitly can be linked to her risk aversion. The higher $\overline{L}$ is set, the the larger aggregate losses need to be before the regulator regulator becomes concerned. 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 in terms of outstanding liabilities of the financial sector.

The next step is to define the SCD, given that a financial crisis has materialized, using the expected shortfall function of (16), and with λ a multiplier of sorts, representing the impact of losses in the financial sector on losses for the wider economy, expressed as GDP decline:

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

On the other hand, if no systemic distress occurs, the public has to bear the Social Cost of Buffers (SCB), which we define as the cost to the economy of imposing $\overline{k}$ capital buffers. Formally, we can write

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

We quantify the SCB defined as 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.[21] Our goal is to quantify thissponse as the relative rate of change term, but without specifying a full-blown macro model:

$$\eta = -\frac{dY/d\overline{k}}{Y} = -\left(\frac{dY}{dC}\frac{C}{Y}\right)\left(\frac{dC}{d\overline{k}}\frac{1}{C}\right) \tag{18}$$

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

[21] 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.

requirement.[22]

Then we can write

$$SCB(\overline{k}) = \eta\left(\overline{k} - \overline{k}_0\right) \tag{21}$$

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

Finally, combining the functional forms of the SCD and the SCB, we can now formulate a *social disutility function SDF* that a policymaker aims to minimize by choosing the target level of macroprudential capitalization:

$$SDF = \min_{\overline{k}} \left\{P(\overline{k})SCD(\overline{k}) + (1 - P(\overline{k}))SCB(\overline{k})\right\} \tag{22}$$

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

$$\frac{\partial P}{\partial \overline{k}}SCD + P\frac{\partial SCB}{\partial \overline{k}} = \frac{\partial P}{\partial \overline{k}}SCB - (1 - P)\frac{\partial SCB}{\partial \overline{k}}$$

Consider next the empirical implementation of this model to our universe of European banks. We do this in two steps: in Section 5.2 we determine the optimal bank-specific macroprudential buffers subject to the current average. Finally, in Section 5.3 we determine the optimal average buffer using the approach derived in 5.1.2.

5.2 The Expected Systemic Shortfall Approach: Empirics

Figure 9 shows the model-based macroprudential rate if they were set on a European scale and compared to the current national O-SII rates. The figure shows that the optimization model prefers to allocate higher buffers consistently to the universe of French and to some extent Spanish banks, while it compensates by allocating lower buffers to the Netherlands and Germany. The discrepancy is largely the result of the objective underlying the current 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 while our optimal approach explicitly takes the euro-wide systemic impact of individual banks into account.

Table (1) shows the results of the same analysis but now applied to the subsample of Dutch banks, their capital buffers are set to the Dutch average. Within a domestic

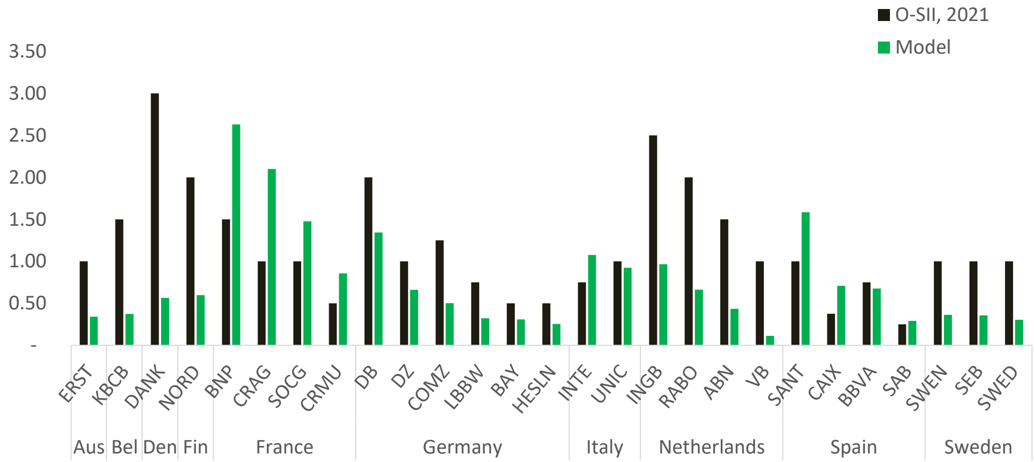
[22] The literature on the long-term impact of capital buffers looks at an alternative approach where the increase in capital buffers raises the cost of lending, and as a result the cost of capital. Miles et al. (2013) for example define the cost of capital increase through the effect a rise in the cost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

$$\frac{dY}{dP_K}\frac{P_K}{Y} = \left(\frac{dY}{dK}\frac{K}{Y}\right)\left(\frac{dK}{dP}\frac{P}{K}\right)\left(\frac{dP}{dP_K}\frac{P_K}{P}\right) \tag{19}$$

$$= \alpha\sigma\frac{1}{1-\alpha} \tag{20}$$

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 sample of 1.25%.. The numerical data underlying this figure are given in Table 4 in Annex A..

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 illustrated earlier, the discrepancy between model recommendations and actual O-SII rates is much more noticeable between countries than within countries.

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

Bank	O-SII Rate	$k^*_{i,macro}(\bar{k}_{osii})$	$k_{i,macro}(\bar{k}=3\%)$
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

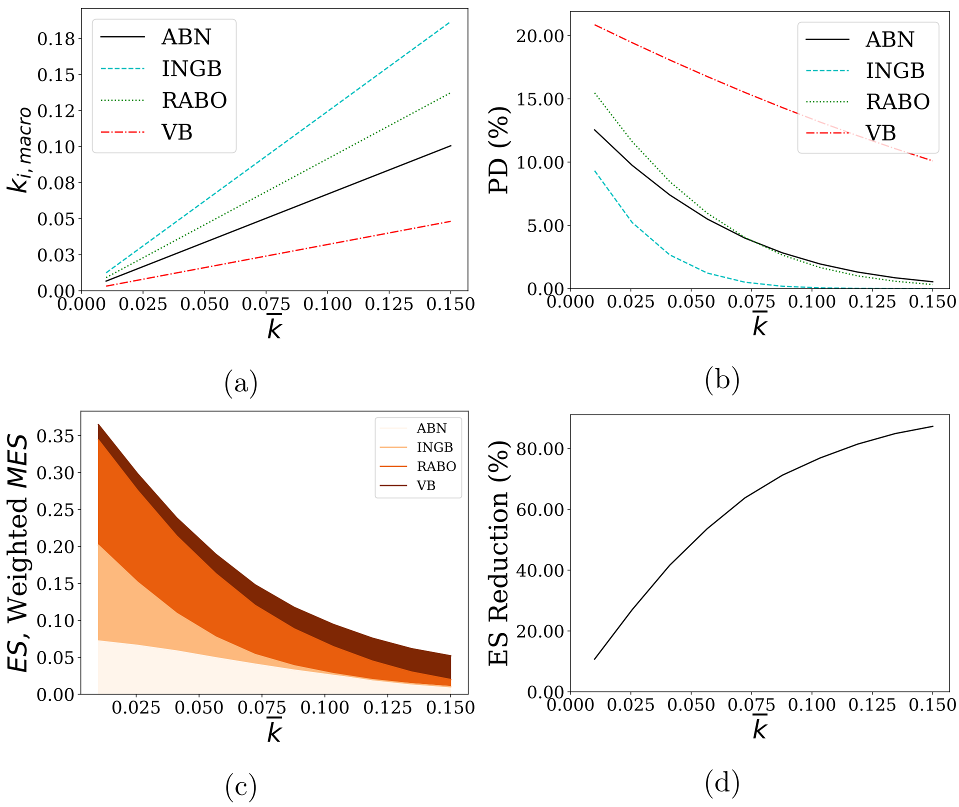
Note. This table shows the actual O-SII macroprudential buffer rates (as of 2021) vs. the model-based rates evaluated at the current weighted average of 2.1% and at an average of 3%.

Figure 10 shows how the results on the four Dutch systemic banks change when we vary the constraint on the average buffer. First of all the Figure shows that the optimal Macroprudential requirements increase linearly with the relaxation of the constraint (see Fig. 10a), while the default probabilities decrease nonlinearly (see Fig. 10b). The contributions of INGB, RABO, ABN and VB to overall risk, expressed by the weighted MES, decrease when the average buffersize goes up (Fig. 10c). As a consequence, total systemic risk, quantified through the ES of the system, decreases as buffers go up: Figure 10d shows the percentage reduction in ES as a function of $\bar{k}$. The percentage reduction in ES is measured relative to the case where only microprudential buffers are set.

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

Finally, we turn to parametrizing the optimization problem (22). The core assumption behind our approach is that increased capitalization requirements will lead to a negative

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.

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.[23] 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 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

[23] Cf. Cline (2017) for an extensive discussion of this approach.

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.[24] 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 look at data from developed and developing economies since the Second World War, and find that on average a banking crisis associated with a recession produces a 9% decline in GDP from peak to through. Of course, significant regulatory changes have been made in Europe since the twin crisis 2008/10, to stave off the occurrence of financial crises. We capture this through the estimation of the probability of a financial crisis from observed CDS data on the creditworthiness of banks, and indeed we show the downward trend in Dimitrov and van Wijnbergen (2023). Conditional on a crisis occurring, however, we still rely on the baseline effect estimated by Reinhart and Rogoff (2009).

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 then 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

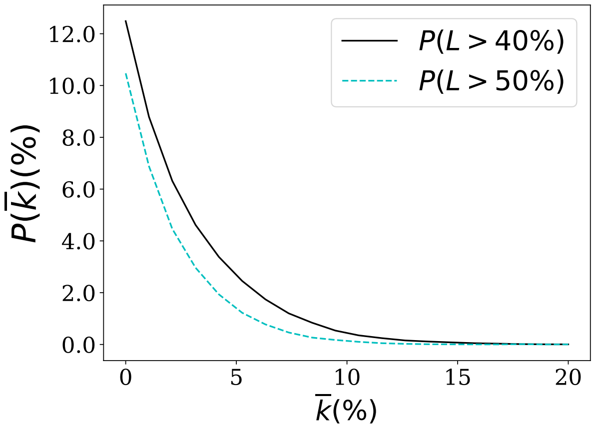
Variable	Value	Source
η	.024	
$(dY/dC)(C/Y)$	.006	Barauskaitė et al. (2022)
$(dC)(d\bar{k})(1/C)$	-.04	Favara et al. (2021)
λ	.18	Implied from Reinhart and Rogoff (2009)

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

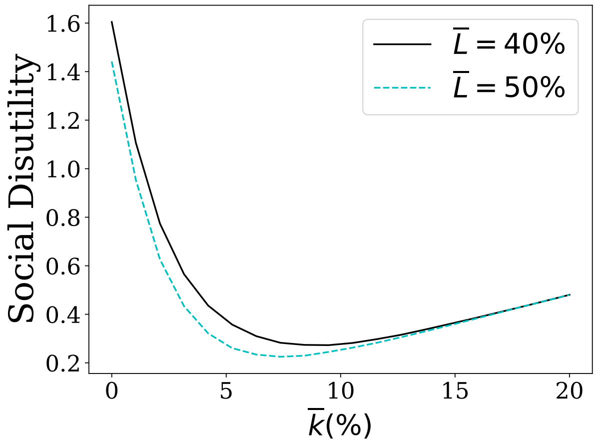
Figure 11 illustrates the results, showing the range of the estimated output costs for the baseline parametrization of the model. As we discussed earlier, the parameter $\overline{L}$ governs the policymaker's tolerance to systemic losses, indicating the aggregate losses as a percentage of the outstanding liabilities, above which by assumption 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 below the threshold before stepping in. Therefore the higher the intervention threshold $\overline{L}$ is, the lower the level of the macro buffers. The two lines in Figure 11 illustrate two cases, one with $\overline{L}$ set equal to 40% and the second set to a higher level of 50%.

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

Figure 11: 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 probability that a financial crisis occurs when it is defined either as banking losses greater than 40% or greater than 50%. Chart (b) shows the resulting social by disutility weighing the costs and benefits of higher buffers.

The two lines in Figure 11a indicate the probability that losses larger than the two target rates occur as a function of the aggregate average macroprudential buffer size $\overline{k}$. Note the high convexity of the probability with respect to the average capital buffers. Once the average buffer add-on is pushed above 10%, $P(\overline{k})$ is reduced virtually to zero.

The other subfigure, Fig.11b, shows the Social Disutility Function SDF from equation 22. Once again there is an inflecion point at around 10%. Above that level the probability of a crisis occurring has been reduced to virtually zero (*vide* Fig.11a) so that above that percentage social disutility is fully driven by just the linear social costs of bearing the higher buffers.

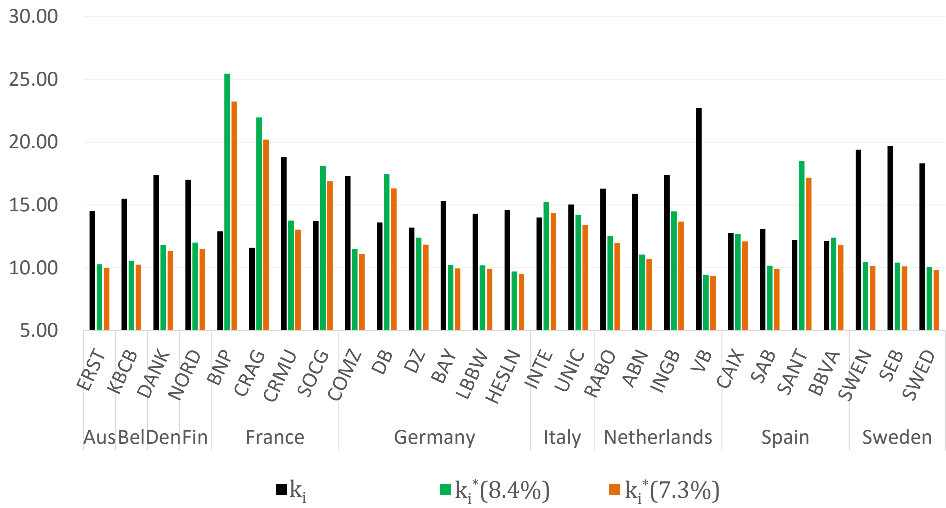
From Figure 11b one can also read the capital buffer average at which the SDF is minimized: at 7.3% in the first case (solid black line), with a high level of $\overline{L} = 50\%$, reflecting lower institutional risk aversion; the second (grey dotted) line reflects a lower $\overline{L} = 40\%$ and a correspondingly higher level of institutional risk aversion. That results in a somewhat higher optimal buffer size of 8.4%. The expected output cost at the minimum point account for .07% in the high buffer case corresponding to $\overline{L} = 40\%$ and a lower .002% in the lower buffer case corresponding to $\overline{L} = 50\%$.

Figure 12 shows the distribution of the total capital buffers from the model across the banks in our European sample, but this time set to average out to the optimal $\overline{k}$. We include both $\overline{L}$ cases and their corresponding optimal average buffer sizes in the sample. In this Figure, we compare the model outcomes not to the required OS-II buffers (as we did in Fig. 9) 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[25].

Once again we obtain similar results, with some areas where banks seem undercapitalized relative to the model 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 universe except Crédit Mutuel (CRMU),

[25]See Annex B for details on these policy frameworks.

Figure 12: Fully 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 optimal $\overline{k}$ of 7.3% and at 6.3% respectively, as established earlier. The numerical data underlying this figure are given in Table 4 in Annex A.

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 with significantly higher capitalization ratios in practice than required by the model.

Interestingly, the two Italian banks in our sample Intesa Sanpaolo (INTE) and Unicredit (UNIC) do not show a significant difference between actual and model outcomes. 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 13a), the two banks are smaller on a European scale (as Table 3 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 buffer due to systemic concerns within Europe.

6 Conclusions

In this paper, we addressed 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.

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 find that a cross-sectional average of 7.3% to 8.4% macroprudential add-on on top of the microprudential requirements of 4.5% minimum, the 2.5% CCB and the bank-specific P2R CET1 component, 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 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.[26] 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, we should maybe address an often-expressed concern from policymakers on the use of market data to guide banks' capital ratios. Market data tends to be volatile and the concern is that this may lead to volatile estimates of the recommended capital ratios. 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

[26] 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.

relaxed after a while. To avoid overshooting in the estimates, a common approach is to take a weighted average over a time window in order to smooth out sharp increases in the ratios when the CDS rates overshoot. A balanced approach is needed between information sensitivity and noise smoothing.

Third, 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 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.

References

Acharya, V. V. and Johnson, T. 2005. Insider trading in credit derivatives. CEPR Discussion Papers 5180, C.E.P.R. Discussion Papers.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. 2017. Measuring systemic risk. *Review of Financial Studies*, 30(1):2–47.

Acharya, V. V., Bergant, K., Crossignani, M., Eisert, T., and Mccan, F. 2022. The anatomy of the transmission of macroprudential policies. *Journal of Finance*, LXXVII (5):2533–2575.

Admati, A. R., DeMarzo, P. M., Hellwig, M. F., and Pfleiderer, P. C. 2013. Fallacies, irrelevant facts, and myths in the discussion of capital regulation: Why bank equity is not socially expensive. *Max Planck Institute for Research on Collective Goods*, 23: 13–7.

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

Andrieş, A. M., Ongena, S., Sprincean, N., and Tunaru, R. 2022. Risk spillovers and interconnectedness between systemically important institutions. *Journal of Financial Stability*, 58:100963. ISSN 1572-3089.

Baker, M. and Wurgler, J. 2015. Do strict capital requirements raise the cost of capital? bank regulation, capital structure, and the low-risk anomaly. *American Economic Review*, 105(5):315–20.

Barauskaitė, K., Nguyen, A. D., Rousová, L., and Cappiello, L. 2022. The impact of credit supply shocks in the euro area: market-based financing versus loans.

BCBS. 2010. An assessment of the long-term economic impact of stronger capital and liquidity requirements. Technical report, Basel: Bank for International Settlements.

Behn, M. and Schramm, A. 2021. The impact of G-SIB identification on bank lending: Evidence from syndicated loans. *Journal of Financial Stability*, 57:100930.

Bharath, S. T. and Shumway, T. 2008. Forecasting default with the Merton distance to default model. *Review of Financial Studies*, 21(3):1339–1369.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics*, 104(3):535–559.

Bolder, D. J. 2018, *Credit-Risk Modelling: Theoretical Foundations, Diagnostic Tools, Practical Examples, and Numerical Recipes in Python.* Springer. ISBN 978-3-319-94687-0.

Brownlees, C. and Engle, R. F. 2017. SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, 30(1):48–79.

Bräuning, F. and Koopman, S. J. 2016. The dynamic factor network model with an application to global credit risk. Working Papers 16-13, Federal Reserve Bank of Boston.

Cappelletti, G., Ponte Marques, A., Varraso, P., Budrys, Ž., and Peeters, J. 2019. Impact of higher capital buffers on banks' lending and risk-taking: evidence from the euro area experiments. Ecb working paper.

Chan-Lau, J. A. and Sy, A. N. 2007. Distance-to-default in banking: A bridge too far? *Journal of Banking Regulation*, 9(1):14–24.

Christensen, J. 2006. Joint estimation of default and recovery risk: A simulation study. Technical report.

Cline, W. R. 2017, *The Right Balance for Banks: Theory and Evidence on Optimal Capital Requirements.* Princeton University Press. ISBN ISBN 9780881327229.

Crosbie, P. and Bohn, J. 2002. Modeling default risk. Technical report, KVN.

Degryse, H., Mariathasan, M., and Tang, T. H. 2020. GSIB status and corporate lending: An international analysis. *Available at SSRN 3642702.*

Dick-Nielsen, J., Gyntelberg, J., and Thimsen, C. 2022. The cost of capital for banks: Evidence from analyst earnings forecasts. *The Journal of Finance*, 77(5):2577–2611.

Dimitrov, D. and van Wijnbergen, S. 2023. Quantifying systemic risk in the presence of unlisted banks: Application to the European financial sector. *Working Paper.*

Duffie, D. 1999. Credit swap valuation. *Financial Analysts Journal*, 55.

Duffie, D. and Singleton, K. J. 1999. Modeling term structures of defaultable bonds. *Review of Financial Studies*, 12(4):687–720.

EBA. 2020. EBA report on the appropriate methodology to calibrate O-SII buffer rates. Policy report, European Banking Authority.

Engle, R. 2018. Systemic risk 10 years later. *Annual Review of Financial Economics*, 10 (1):125–152.

ESRB. 2017. Final report on the use of structural macroprudential instruments in the EU. Policy report, European Systemic Risk Board.

ESRB. 2021. Annual report. Policy report, European Systemic Risk Board.

Favara, G., Ivanov, I., and Rezende, M. 2021. GSIB surcharges and bank lending: Evidence from us corporate loan data. *Journal of Financial Economics*, 142(3):1426–1443.

Firestone, S., Lorenc, A., and Ranish, B. 2017. An empirical economic assessment of the costs and benefits of bank capital in the us.

FRB. 2015. Calibrating the GSIB Surcharge. Technical report, Federal Reserve Board.

Geiger, S., Heires, M., Krüger, U., Ludwig, J., and Vogel, U. 2022. Calibrating capital buffers for other systemically important institutions (O-SIIs) in germany–utilising the equal expected impact approach. Technical report, Deutsche Bundesbank Technical Paper.

Gibson, M. S. 2004. Understanding the risk of synthetic CDOs. *Finance and Economics Discussion Series*.

Glasserman, P. and Young, H. P. 2016. Contagion in financial networks. *Journal of Economic Literature*, 54(3):779–831.

Gornicka, L. and van Wijnbergen, S. 2013. Financial Frictions and the Credit Transmission Channel: Capital Requirements and Bank Capital. Tinbergen Institute Discussion Papers 13-013/VI/DSF50, Tinbergen Institute.

Gropp, R., Vesala, J., and Vulpes, G. 2006. Equity and bond market signals as leading indicators of bank fragility. *Journal of Money, Credit and Banking*, 38(2):399–428. ISSN 00222879, 15384616.

Harada, K., Ito, T., and Takahashi, S. 2013. Is the distance to default a good measure in predicting bank failures? a case study of japanese major banks. *Japan and the World Economy*, 27:70–82.

Huang, X., Zhou, H., and Zhu, H. 2009. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, 33(11):2036–2049.

Huang, X., Zhou, H., and Zhu, H. 2012. Systemic risk contributions. *Journal of Financial Services Research*, 42(1):55–83.

Hull, J. and White, A. 2004. Valuation of a cdo and an nth to default CDS without monte carlo simulation. *Journal of Derivatives*, 12:8–23.

Hull, J. C. 2018, *Risk Management and Financial Institutions*. John Wiley & Sons. ISBN 978-1-119-44811-2.

Jackson, M. O. and Pernoud, A. 2021. Systemic risk in financial networks: A survey. *Annual Review of Economics*, 13(1):171–202.

Jakucionyte, E. and van Wijnbergen, S. 2018. Unclogging the credit channel: On the macroeconomics of banking frictions.

Jiron, A., Passmore, W., and Werman, A. 2021. An empirical foundation for calibrating the G-SIB surcharge.

Kaserer, C. and Klein, C. 2019. Systemic risk in financial markets: How systemically important are insurers? *Journal of Risk & Insurance*, 86(3):729–759.

Lando, D. 2004, *Credit risk modeling: theory and applications*. Princeton University Press. ISBN 0691120358.

Lehar, A. 2005. Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, 29(10):2577–2603.

Leland, H. E. 1994. Corporate debt value, bond covenants, and optimal capital structure. *Journal of Finance*, 49(4):1213–1252.

Malherbe, F. 2020. Optimal capital requirements over the business and financial cycles. *American Economic Journal: Macroeconomics*, 12(3):139–74.

Mankart, J., Michaelides, A., and Pagratis, S. 2020. Bank capital buffers in a dynamic model. *Financial Management*, 49(2):473–502.

McNeil, F. R., Alexander J. and Embrechts, P. 2005, *Quantitative Risk Management: Concepts, Techniques and Tools*. Princeton University Press. ISBN 0-691-12255-5.

Merton, R. C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2):449–470.

Miles, D., Yang, J., and Marcheggiano, G. 2013. Optimal bank capital. *The Economic Journal*, 123(567):1–37.

Pan, J. and Singleton, K. J. 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. *Journal of Finance*, 63(5):2345–2384.

Pascual, A. G., Avesani, M. R. G., and Li, M. J. 2006. A new risk indicator and stress testing tool: A multifactor nth-to-default CDS basket. IMF Working Papers 2006/105, International Monetary Fund.

Passmore, W. and von Hafften, A. H. 2019. Are Basel's capital surcharges for global systemically important banks too small? *57th issue (March 2019) of the International Journal of Central Banking*.

Pelger, M. 2020. Understanding systematic risk: a high-frequency approach. *The Journal of Finance*, 75(4):2179–2220.

Puzanova, N. and Düllmann, K. 2013. Systemic risk contributions: A credit portfolio approach. *Journal of Banking & Finance*, 37(4):1243–1257.

Reinhart, C. M. and Rogoff, K. S. 2009. The aftermath of financial crises. *American Economic Review*, 99(2):466–72.

Russo, V., Lagasio, V., Brogi, M., and Fabozzi, F. J. 2020. Application of the Merton model to estimate the probability of breaching the capital requirements under basel iii rules. *Annals of Finance*, 16(1):141–157.

Schroth, J. 2021. Macroprudential policy with capital buffers. *Journal of Monetary Economics*, 118:296–311.

Segoviano, M. A. and Goodhart, C. 2009. Banking stability measures. *IMF Working paper WP/09/4*.

Tarashev, N. A. and Zhu, H. 2006. The pricing of portfolio credit risk. BIS Working Papers 214, Bank for International Settlements.

Toader, O. 2015. Estimating the impact of higher capital requirements on the cost of equity: an empirical study of european banks. *International Economics and Economic Policy*, 12(3):411–436.

Vasicek, O. 1987. Probability of loss on loan portfolio. Technical report.

Zhou, C. 2010. Are banks too big to fail? Measuring systemic importance of financial institutions. *International Journal of Central Banking*, 6(34):205–250.

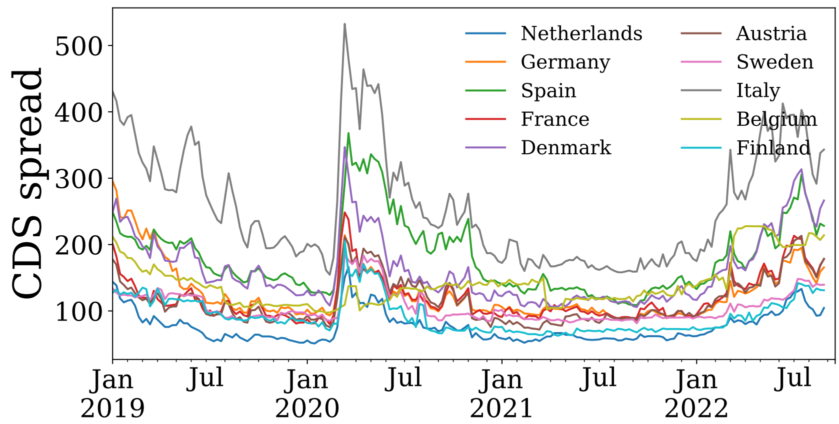
A Input Data and Model Outcomes

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.[27] In line with the rest of the buffers in this study, we only consider the CET1 portion of the P2R framework.

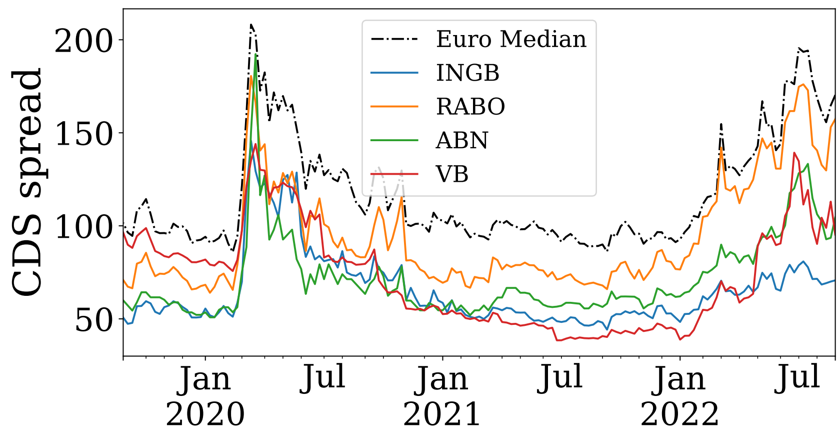
A three-factor latent model is then estimated based on weekly CDS data in the period from August 2019 to August 2022. The number of factors were chosen as a scree plot of the Principle Components of the data showed that three latent factors capture more than 80% of the co-variation in the movements of 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 13 shows the evolution of the CDS spreads in our sample for the evaluation period.

Figure 13: CDS Prices (bps)



(a) Median Rates per Country



(b) Dutch Banks

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

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

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 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 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}	k_{P2R}
Austria	ERST	Erste Group	1.51	100.00	79.80	1.71	0.93	0.03	0.03	7.50	14.50	0.98
Belgium	KBCB	KBC	1.67	100.00	214.03	2.03	0.15	0.13	(0.15)	8.30	15.50	1.05
Denmark	DANK	Danske Bank	2.66	100.00	266.43	2.50	0.95	0.09	0.10	9.76	17.40	1.01
Finland	NORD	Nordea	2.82	100.00	131.16	1.27	0.61	(0.69)	0.20	8.40	17.00	0.98
France	BNP	BNP Paribas	13.24	37.59	163.10	1.57	0.96	0.20	0.05	6.54	12.89	0.74
France	CRAG	Credit Agricole	10.51	29.85	156.92	1.51	0.95	0.23	0.07	5.84	11.60	0.84
France	CRMU	Credit Mutuel	4.15	11.79	206.83	1.97	0.51	0.09	(0.06)	10.10	18.80	0.98
France	SOCG	Societe Generale	7.32	20.78	192.76	1.84	0.93	0.18	0.06	7.18	13.71	1.19
Germany	COMZ	Commerzbank	2.33	14.61	317.91	2.95	0.95	0.17	(0.02)	7.84	13.60	1.13
Germany	DB	Deutsche Bank	6.64	41.68	328.06	3.03	0.92	0.13	(0.08)	7.66	13.20	1.41
Germany	DZ	DZ Bank	3.14	19.74	49.95	1.43	0.86	0.01	0.09	7.68	15.30	0.96
Germany	BAY	Bayern LB	1.34	8.43	64.24	1.57	0.92	(0.07)	0.02	8.87	17.30	1.13
Germany	LBBW	LBBW	1.41	8.84	51.96	1.45	0.91	(0.02)	0.08	7.34	14.60	1.03
Germany	HESLN	Helaba	1.07	6.70	69.33	1.61	0.92	(0.06)	0.08	7.32	14.30	0.98
Italy	INTE	Intesa Sanpaolo	5.28	54.04	323.84	3.00	0.92	0.13	0.07	8.11	14.00	1.01
Italy	UNIC	Unicredit	4.49	45.96	362.50	3.32	0.92	0.11	0.03	8.93	15.03	0.98
Netherlands	RABO	Rabobank	3.15	30.94	157.35	1.51	0.95	0.15	0.07	8.87	17.40	1.07
Netherlands	ABN	ABN Amro	1.99	19.54	104.46	1.02	0.72	0.00	(0.29)	7.76	16.30	1.13
Netherlands	INGB	ING	4.71	46.22	70.71	0.69	0.74	(0.07)	0.12	7.13	15.89	0.98
Netherlands	VB	Volksbank	0.34	3.30	95.29	0.93	0.65	0.11	(0.21)	10.90	22.70	1.69
Spain	CAIX	Caixabank	3.38	21.51	225.64	2.14	0.19	(0.08)	(0.49)	7.05	13.10	0.93
Spain	SAB	Sabadell	1.25	7.97	365.34	3.35	0.30	(0.09)	(0.64)	7.24	12.22	1.21
Spain	SANT	Santander	7.87	50.03	214.60	2.04	0.96	0.15	(0.01)	6.46	12.12	0.84
Spain	BBVA	BBVA	3.22	20.49	230.76	2.18	0.94	0.16	(0.02)	6.89	12.75	0.84
Sweden	SWEN	Handelsbanken	1.61	35.70	133.98	1.30	0.69	(0.62)	0.05	9.70	19.40	1.01
Sweden	SEB	SEB	1.59	35.09	139.54	1.35	0.65	(0.71)	0.03	9.92	19.70	1.01
Sweden	SWED	Swedbank	1.32	29.20	164.63	1.58	0.66	(0.37)	(0.27)	9.43	18.30	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 4 shows the optimal model capitalization rates per bank.

Table 4: Model Output Data

		At O-SII average		At optimal $\overline{k}$		
Country	Short Code	k_{O-SII}	$k^*_{i,macro}(\overline{k}_{O-SII})$	k_i^{CET1}	$k_i^*(\overline{k}=8.4)$	$k_i^*(\overline{k}=7.3)$
Austria	ERST	1.00	0.34	14.50	10.28	9.99
Belgium	KBCB	1.50	0.37	15.50	10.56	10.24
Denmark	DANK	3.00	0.57	17.40	11.82	11.34
Finland	NORD	2.00	0.60	17.00	12.01	11.50
France	BNP	1.50	2.63	12.89	25.45	23.23
	CRAG	1.00	2.10	11.60	21.97	20.20
	CRMU	0.50	0.86	18.80	13.75	13.03
	SOCG	1.00	1.48	13.71	18.12	16.88
Germany	BAY	1.25	0.50	17.30	11.49	11.07
	COMZ	2.00	1.34	13.60	17.44	16.31
	DB	1.00	0.66	13.20	12.40	11.84
	DZ	0.50	0.31	15.30	10.20	9.94
	HESLN	0.75	0.32	14.30	10.19	9.92
	LBBW	0.50	0.26	14.60	9.70	9.48
Italy	INTE	0.75	1.08	14.00	15.25	14.35
	UNIC	1.00	0.92	15.03	14.19	13.42
Netherlands	ABN	2.00	0.66	16.30	12.52	11.96
	INGB	1.50	0.44	15.89	11.05	10.69
	RABO	2.50	0.97	17.40	14.48	13.67
	VB	1.00	0.11	22.70	9.44	9.35
Spain	BBVA	0.38	0.71	12.75	12.69	12.09
	CAIX	0.25	0.29	13.10	10.17	9.92
	SAB	1.00	1.58	12.22	18.50	17.17
	SANT	0.75	0.68	12.12	12.39	11.82
Sweden	SWEN	1.00	0.36	19.40	10.44	10.14
	SEB	1.00	0.36	19.70	10.41	10.11
	SWED	1.00	0.30	18.30	10.06	9.80

Note. This table shows the optimal buffers based on the model output. The columns show for each bank in the universe the O-SII capital buffer rate for 2022, the model-based buffer rate at the current O-SII weighted average, the total CET1 capitalization for 2022, the model-based capitalization at the optimum $\overline{k}$ of 8.4% and 7.3%.

B Regulatory Capital Requirements

Here we provide a short overview of the different regulatory capital requirements[28]

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.

[28] 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.

- 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.

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.[29]

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

[29] 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.

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.