Macroprudential Regulation: A Risk Management Approach

Systemic Risk in the European Financial Sector

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Agenda

1. Motivation
2. Related literature
3. Build a Model of the Banking System and Capital Buffers
    - Gaussian Copula and Merton Dynamics
    - Calibration based on CDS prices
4. Optimal Macroprudential Buffers: Application on a universe of key European banks:
    - Equalizing Expected Equal Impact (EEI)
    - Minimizing Expected Systemic Shortfall (ESS)
    - The Optimal Level of Target Average Buffers

Motivation

1. **Risk Measurement** (Dimitrov/van Wijnbergen, 2022/23): identify systemically relevant ("TBTF") institutions and attribute systemic risk proportions
    - Regulatory approach: O-SII (domestic) and G-SII (global banks); Score and rank banks by: Size, Importance, Complexity/cross-border activity, Interconnectedness
    - Academic approach: market data driven
        - this paper: look at credit risk dependencies
2. **Risk Management** (current paper): reduce banks' contribution to systemic risk by managing macroprudential buffers
    - Policy approach: Equal Expected Impact (EEI)
        - Mapping the scores to capital buffers very heterogeneous approaches within EU countries (O-SII)
    - Academic approaches not well explored

2. Related Literature

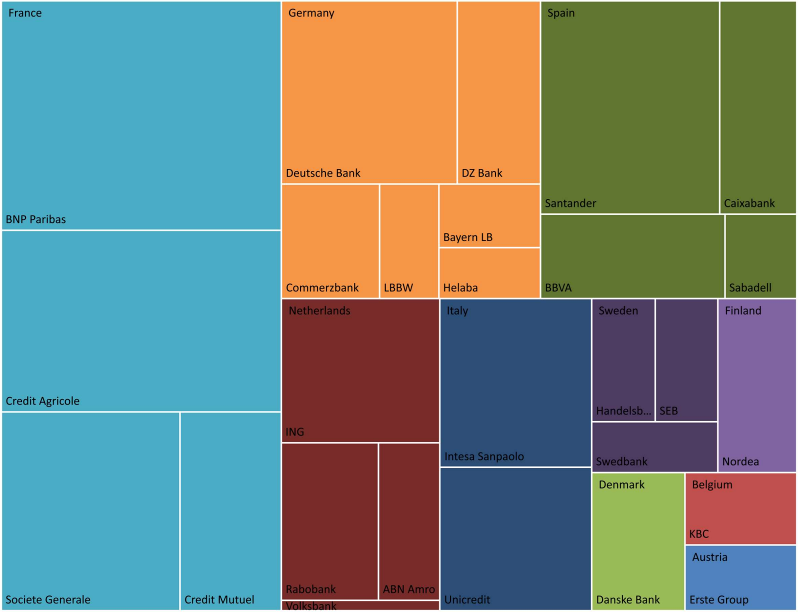
- Wide academic literature on measuring systemic risk (CoVaR: *Adrian/Brunnermeier, 2016*; MES: *Acharya, 2017*; SRISK: *Engle, 2018*; DIP: *Huang et al., 2012*; *Lehar, 2005*, etc.)

- Macroprudential literature mostly on banks' housing exposures and leverage constraints for borrowers: *Acharya, 2022*
- Earlier literature on Economic Cost of Capital: *Miles eA, 2013; Cline, 2017; Firestone eA, 2017*
- Macro literature on bank capital: *Malherbe, 2020; Schroth, 2021; Mankart eA 2020*
- Modelling default correlations: *Tarashev/Zhu, 2006; Hull/White, 2004; Vasicek, 1987*
- Distance-to-Default and bank fragility: *Harada eA, 2013; Chan-Lau Sy, 2007, Bharath, 2008*, etc.

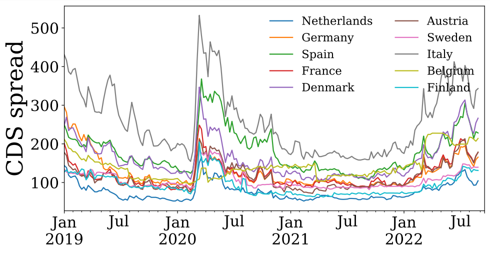
Empirical Application

- Universe of 27 large European banks (O-SII and G-SII).
- Evaluation date: Aug, 29, 2022
- Correlation time window: 3 years
- Dataset: CDS spreads on subordinate debt; Balance sheet liability sizes

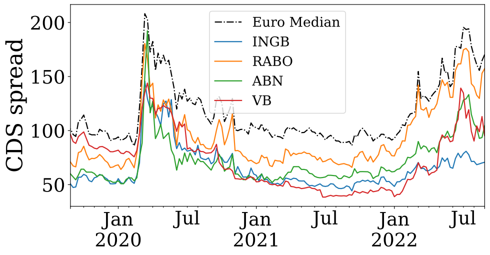
Relative Liability Size



CDS Prices



(a) Median Rates per Country



(b) Dutch Banks

A Model of Bank Distress: Overview

- Regulate the risk of the simultaneous defaults of multiple banks
- Using CDS data to imply risk
    - Levels of the CDS price speaks about the market view on the credit-worthiness of the institution
    - Co-movements in default probabilities (single-name CDS prices) speak about the tendency of banks to be exposed to the same risk drivers
- Combine tools from the securitization and from the banking literature
    - Merton type **Distance-to-Default**: Probability of Default (PD) is a function of the capitalization and asset variance
    - (Gaussian) **Factor Copula** Approach to capture default dependencies: systematic co-variation and idiosyncratic variation of default
    - can be extended to allow for asymmetries and fat tails

Excursion on CDS prices

- CDS: insurance derivative contract (OTC) on default of an underlying
- Typically traded on standardized T&Cs (maturities, the definition of a credit event, etc.)
- Linked directly to default risks of the company
  - Since 2014 ISDA definition of a credit event also *includes restructuring* and *government intervention*.
- The CDS market is more liquid and has *fewer trading frictions than the bond market*
- An *edge over credit rating agencies*
- Some evidence CDS prices may lead the equity markets in price discovery
  - Insiders active on the CDS market, *Acharya & Johnson [2005]*
- Alternatives exist:
  - Equity based; What about non-listed banks (e.g. the Rabo...)?
  - Balance-sheet based (Z-Scores ?); How predictive are they really?

3. A Model of Bank Distress

U_i is an (unobserved) credit-worthiness variable s.t.

$$U_i \sim N(0, 1)$$

Default occurs if:

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

with X_i representing a fixed default threshold (quasi-observed)

$$\implies PD_i \equiv \Phi(X_i)$$

with $\Phi(.)$ the standard normal distribution

Excursion on Implying PDs from CDS quotes

- We can't rely on observations of default (defaults of systemic institutions are very rare)
- ... but we quasi-observe banks' default probabilities (PD) through the CDS market, [Duffie, 1999]
- By convention the swap has zero value at contract initiation:

$\implies$ Value of CDS premia payments in survival = Expected value of protection in default

$$\underbrace{CDS_t \int_t^{T_{cds}} e^{-r_\tau \tau} \Gamma_\tau d\tau}_{\text{PV of CDS premia in survival}} = \underbrace{(1 - ERR_t) \int_t^{T_{cds}} e^{-r_\tau \tau} q_\tau d\tau}_{\text{PV of protection payment in default}} \tag{2}$$

- Assume fixed interest rate r_t, default intensity q_t. Solve for q_t
- Set $PD_i = q_t$

- *Systemic risk implies*: defaults need to be evaluate in the context of other banks defaulting
- Latent factor model drives default correlations:

$$U_i = \rho_i M + \sqrt{1 - \rho_i \rho_i'} Z_i \tag{3}$$

$M = [m_1, \dots m_f]'$ is a vector of f common latent factors, and Z_i is the bank-specific factor $(M, Z_i \sim N(0,1))$, $\rho_i = [\rho_{i,1}, ..., \rho_{i,f}]$ is a vector of factor loadings, such that $\rho_i \rho_i' \leq 1$.

Excursion on Factor Exposures Estimation

Estimate all ρ_i, ρ_j relative to a target correlation matrix

$$\min_{\rho_i,\ldots,\rho_j} \sum_{i=2}^{N} \sum_{j=1}^{N} (a_{ij} - \rho_i \rho_j')^2 \tag{4}$$

with target correlations a_{ij} evaluated from co-movements in banks' PDs [Cf. Tarashev & Zhu, 2006; Andersen eA, 2003]

We need structure to related CDS spread changes over time to asset correlations $a_{ij} \implies$ Merton's firm model

Excursion on the Merton Model

- Assume the Merton firm model (under the r.n. distribution) holds

$$d \ln V_{i,t} = rdt + \sigma_i dW_{i,t} \tag{5}$$

where $V_{i,t}$ is the (unobserved) risk-weighted asset value of bank i; r is the risk-free rate; $dW_{i,t}$ is a Brownian Motion.

- Default occurs if assets fall below value of debt

$$PD_{i,t} = \mathbb{P}(V_{i,t+T} \leq D_i) \tag{6}$$

$$\implies DD_{i,t} = \frac{\ln \frac{V_{i,t}}{D_i} + \left(r - \frac{\sigma_i^2}{2}\right) T}{\sigma_i \sqrt{T}} \tag{7}$$

- Combining (1) and (7) : $PD_{i,t} = \mathbb{P}\left(\underbrace{\frac{W_{i,t+T}}{\sqrt{T}}}_{U_i} \leq \underbrace{-DD_{i,t}}_{X_i}\right)$

The Merton Model and Target Correlations

No need to estimate $V_{i,t}; DD_{i,t}$ but model has important implications

1. Target asset corrs:

$$a_{ij} = \mathbb{Corr}(\Delta\Phi^{-1}(-PD_{i,t}), \Delta\Phi^{-1}(-PD_{i,t}))$$

Three factor model captures the common variation in the the CDS data well.

A Model of the Bank Distress

2. DD is related to bank's capitalization

$$DD(k_i;\sigma_i) = \frac{-\ln(1-k_i) + \left(r - \frac{1}{2}\sigma_i^2\right)}{\sigma_i} \tag{8}$$

with $k_i = E_i/D_i$, corresponding to CET1 capital; σ_i is st.dev. of bank's RWAs, r is the risk-free rate

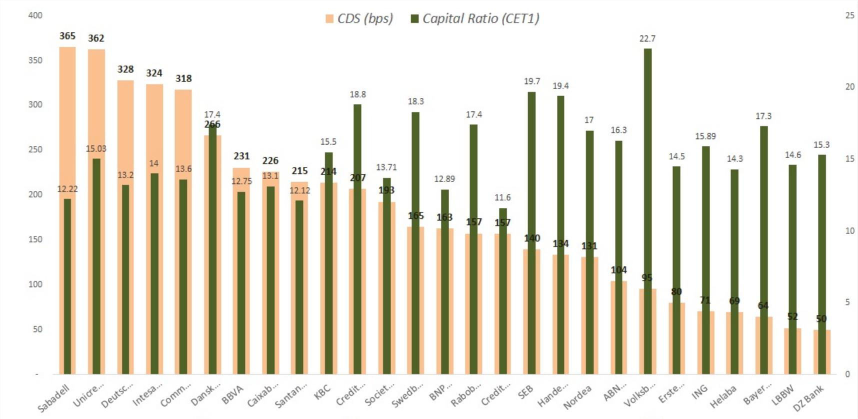
$$\implies PD_i = \Phi\left(-DD(k_i;\sigma_i)\right) \tag{9}$$

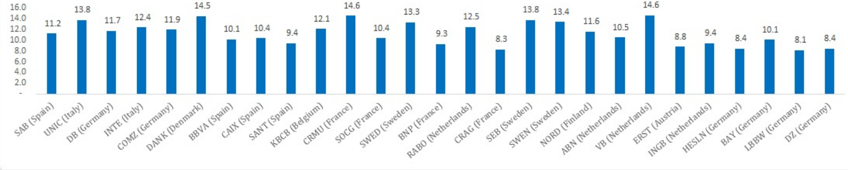
- Two purposes of (9):
    1. Given current PD_i and k_i imply σ_i
    2. Given σ_i, vary k_i and observe effect on bank's $PD \implies$ evaluate the effect on the system

Factor Loadings

		F1	F2	F3
Aus	**ERST**	0.93	0.02	0.04
Bel	**KBCB**	0.15	0.13	(0.14)
Den	**DANK**	0.95	0.09	0.11
Fin	**NORD**	0.61	(0.69)	0.20
France	**SOCG**	0.93	0.18	0.07
	BNP	0.96	0.20	0.06
	CRAG	0.95	0.23	0.07
	CRMU	0.51	0.09	(0.06)
Germany	**DZ**	0.86	0.01	0.10
	HESLN	0.92	(0.06)	0.08
	COMZ	0.95	0.16	(0.01)
	BAY	0.92	(0.07)	0.03
	DB	0.92	0.13	(0.08)
	LBBW	0.91	(0.03)	0.09
Italy	**UNIC**	0.92	0.11	0.05
	INTE	0.92	0.12	0.08
Netherlands	**RABO**	0.95	0.15	0.08
	ABN	0.72	0.00	(0.29)
	INGB	0.74	(0.07)	0.12
	VB	0.65	0.11	(0.21)
Spain	**CAIX**	0.19	(0.08)	(0.49)
	SAB	0.30	(0.09)	(0.64)
	SANT	0.96	0.15	(0.00)
	BBVA	0.94	0.16	(0.02)
Swed	**SWEN**	0.69	(0.62)	0.05
	SEB	0.65	(0.71)	0.02
	SWED	0.66	(0.36)	(0.28)

CDS Spreads, Capitalization and Implied Variance





4. Macroprudential Policy

- So far, we were in the domain of credit risk
- Now, apply to systemic risk and macroprudential regulation (main innovation of this paper)
- Total required capitalization

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

- Macroprudential regulation: determine the optimal $k_{i,macro}$ based on bank's systemic relevance for given $k_{i,micro}$

Optimal Macro Buffers: Approaches

1. Equal Expected Impact approach
    - define a probabilistic systemic cost of default (SCD) function
    - equalize SCDs between a SII and a reference non-SII
2. Risk minimization approach
    - Minimize systemic risk by allocating a capital buffer "budget" (average)
3. Determine the size of the socially optimal budget through cost-benefit analysis of higher buffers

PDs and Systemic Risk

Define a cost function associated with systemic risk (Systemic Cost of Default, with EL_i as Expected Loss):

$$SCD_i = EL_i + \sum_{j \neq i} (EL_{j|i} - EL_j) PD_i$$

or in relative terms:

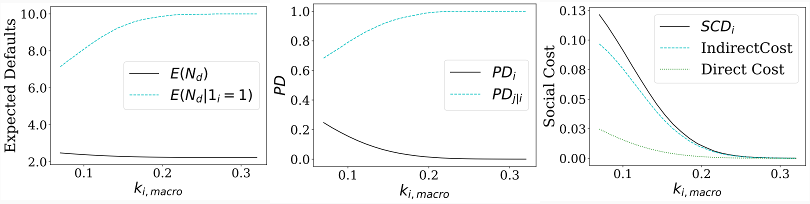
$$SCD_i = \underbrace{w_i LGD_i PD_i}_{\text{Direct Cost (Microprudential)}} + \underbrace{\sum_{j \neq i} w_j LGD_j \left(PD_{j|i} - PD_j \right) PD_i}_{\text{Indirect Cost (Macroprudential)}} \quad (10)$$

w_i relative liability size (EAD for the regulator); PD_i default probab.; $PD_{j|i}$ conditional default of j given i defaults; LGD_i Loss Given Default (assume 100%); SCD_i is relative to the total size of the banking system (total liabilities)

Quantitative Example

Assume a financial system of ten homogeneous banks. Increase the capitalization of bank i.

Figure 3: Capital Requirements

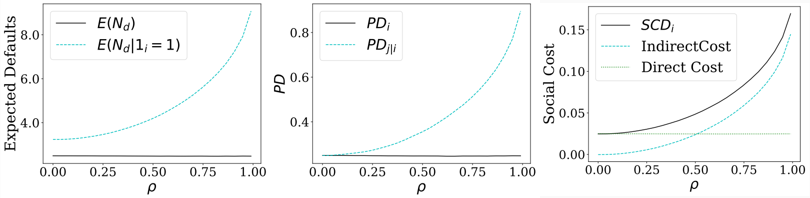


(a) Number of Defaults **(b)** Default Probabilities **(c)** Systemic Cost

Quantitative Example

Assume a financial system of ten homogeneous banks ($\rho_i = \rho$)

Figure 5: Asset Correlation



(a) Number of defaults **(b)** Default Probabilities **(c)** Systemic Cost

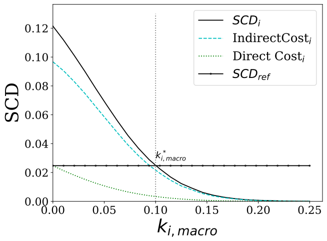
EEI Approach

1. Construct a benchmark non-systemic institution (no indirect cost associated with it)

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

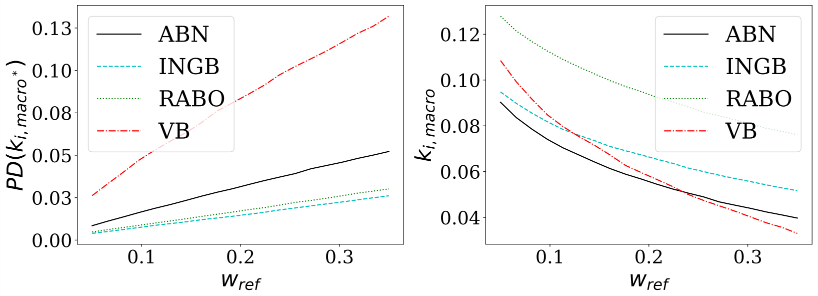
2. Set macro buffers to equalize the reference social cost with that of the systemic institution subject to macro add-on

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



Empirical Application to the Dutch Sub-sample

Figure 7: Optimal Macro Buffers



(a) **(b)**

- Rankings are stable but levels depend on choice of w_{ref}
- EEI approach puts
  - high emphasis on distress correlations
  - high emphasis on asset variance
  - lower emphasis on size

4.2. Expected Shortfall Approach

Second approach:

- The financial system can be seen as a portfolio of long loan positions
- *Idea:* Evaluate and manage through capital buffers the credit risk of this portfolio
- Formally, define credit losses as

$$\begin{aligned} L_i &= \mathbb{1}_i LGD_i \\ L_{sys} &= \sum_{i=1}^{N} w_i L_i \end{aligned} \tag{13}$$

- Define Expected Shortfall [Acharya eA, 2017; Huang eA 2012]

$$ES_{sys} = \mathbb{E}\left(L_{sys} | L_{sys} > \overline{L}\right) \tag{14}$$

- Minimize system's potential default losses (Expected Shortfall) by increasing macro capital requirements s.t. a target

The policymaker problem:

$$\begin{aligned} \min_{k_{\mathbf{1},macro},\ldots,k_{N,macro}} \quad & ES_{sys}(k_{micro}; k_{1,macro}, \ldots, k_{N,macro}) \\ s.t. \sum_i w_i k_{i,macro} &= \overline{k} \end{aligned} \tag{15}$$

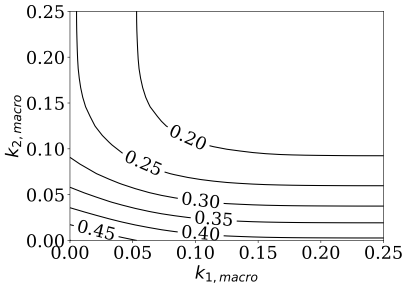


Figure 9: Expected Shortfall, Example

4.2. ES Approach: Empirical results

Calibrate to current O-SII buffer average $\overline{k}_{osii}$ for the Netherlands

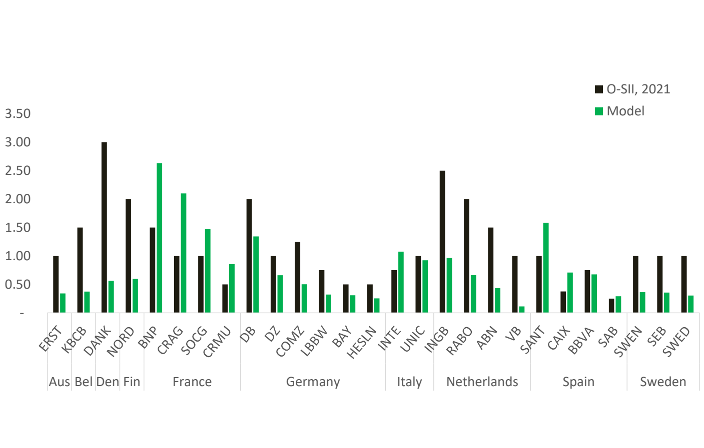
Table 1

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

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

Calibrate to current O-SII buffer average in the Euro sample

Figure 10: Optimal Macro Buffers at current O-SII average



4.3. How high should $\overline{k}$ be?

- Define an overarching policymaker objective
- Choose $\overline{k}$ to balance
  - the social costs of default given that systemic distress occurs (SCD) with probability $P(\overline{k})$
  - and the social costs of higher buffers (SCB) given that no system-wide distress occurs
- Probability of distress conditional on optimal allocation of capital buffers between banks in line with (15)

How high should $\overline{k}$ be?

Formally, we can write a disutility function:

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

where

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

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

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

with λ as macro multiplicator for financial losses and η as the sensitivity of aggregate output to capital buffers, which can be decomposed into

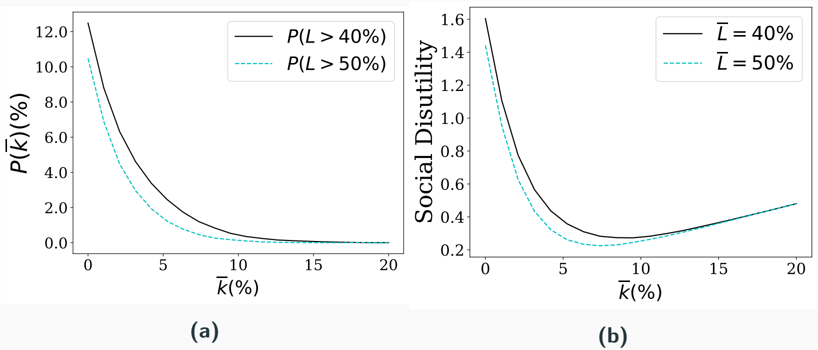
$$\eta = -\frac{dY/d\overline{k}}{Y} = -\left(\frac{dY}{dC} \frac{C}{Y} \right) \left(\frac{dC}{d\overline{k}} \frac{1}{C} \right) \tag{16}$$

4.3. Calibrating $\overline{k}$

- λ: Reinhart/Rogoff, 2009: Banking crises produce 9% GDP decline on average. Assumed $LGD = 100\%$. Assuming banking crisis occurs if 1/2 of the sector is in distress $\implies \lambda = \frac{9\%}{.5 \cdot 100\%} = .18$
- $(dY/dC)(C/Y)$: Brauskaite eA, 2022: 1% reduction in loan supply results in .6% decline in GDP growth
- $(dC)(d\overline{k})(1/C)$: Favara eA, 2021: 1% incremental increase in macro capital, leads to 3-4% decline in lending of the targeted banks

4.3. Calibrating $\overline{k}$

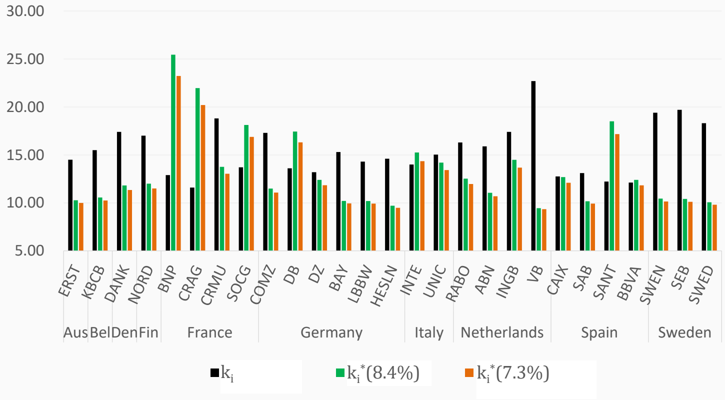
Figure 12: Macroprudential Cost Calibration



For reasonable calbration $\overline{k}$ between 7.3% and 8.4% depending on the loss-aversion of the regulator.

4.2. ES Approach: Empirical results

Figure 14: Total Optimal Buffers, at current socially Optimal $\overline{k}$



Summary

- Develop quantitative data-based framework to calibrate macroprudential buffers
  - EEI: equalizing systemic costs of default
  - ES: Minimizing systemic risk relative to an aggregate capital target ratio
- Implications: EEI approach
  - produces more conservative results than current O-SII framework in the NL
  - blends sensitivity and contribution to systemic risk
  - puts emphasis on distress dependencies and asset risk
- Implications: Minimizing ES
  - Practical and flexible implementation.
  - Calibrate current O-SII rates
  - Calibrate to a social optimum
  - Both show substantial heterogeneity across European countries on O-SII rates when calibrated to European average
  - the French are the real outliers (too low?)

Potential Further Work

- Embed network structure to allow for non-symmetric risk spillovers
- Look into spillover channels from the financial network to the real economy
- A VAR approach to determine which banks are leading in risk
- Separate cyclical from structural components of systemic risk
  - Relate the model to counter-cyclical buffers
- Use the framework to assess sovereign risk spillovers
- Use the framework to assess climate-related financial risks

Annex: Dutch Sub-sample

Name	w_c(%)	CDS (bps)	PD(%)	ρ_1	ρ_2	ρ_3	$\hat{\sigma}$	k_{CET1}(%)
ING	46.22	70.71	3.25	0.73	0.10	0.15	0.09	15.89
Rabobank	30.94	157.35	6.58	0.95	(0.12)	0.12	0.12	17.40
ABN Amro	19.54	104.46	4.62	0.73	0.00	(0.27)	0.11	16.30
Volksbank	3.30	95.29	4.26	0.67	(0.10)	(0.19)	0.15	22.70

Note. w_c: liability size on a domestic scale ;ρ_1; ρ_2; ρ_3: factor exposures; $\hat{\sigma}$: implied st.dev. of RWAs

Annex: Full Sample

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