Quantifying Systemic Risk in the Presence of Unlisted Banks

Application to the Dutch Financial Sector

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Motivation

- Macroprudential policy widely acknowledged to be of prime importance but implementation tends to be *ad hoc*
- Academic approach: imply tail dependencies using equity market data, e.g. *Adrian/Brunnermeier [2016]* and *Acharya [2017]*
- Key challenge: many European banks are not publicly traded on the equity market
- … but they are traded on the Credit Default Swaps (CDS) market
    - CDS approach by Huang et al. [2012] but add correlated losses in default

Extra benefits of using CDS data

- CDS: insurance derivative contract (OTC) on default of an underlying
- 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
- Typically traded on standardized T&Cs (maturities, the definition of a credit event, etc.)
- Some evidence CDS prices may lead the equity markets in price discovery
  - Insiders active on the CDS market, *Acharya & Johnson [2005]*

Related Literature

- Implying systemic risk from market data
  - CoVaR: Adrian & Brunnermeier, 2016; SRISK: Engle, 2018;
  - MES: Acharya et al., 2017; DIP: Huang et al., 2012;
  - Lehar, 2005; Segoviano and Goodhart, 2009; Zhou,2010; [..]
- Structured Credit Risk: Merton, 1974; Leland, 1994;
- Credit Portfolio Valuation: Vasicek, 1987; Tarashev and Zhu, 2006;
- Financial Stability
  - Distance-to-default: Bharath and Shumway, 2008; Jessen and Lando, 2015
  - Default feedback loops: Acharya et al., 2014
- Theoretical backing
  - Fire sales: Shleifer and Vishny, 1992;
  - Correlated assets (like in Adrian/Brunnermeier (2016), Acharya e.a.(2017))

Modelling Approach Borrows from Securitization Literature

- The regulatory space is viewed as a portfolio of loans
- Distress is defined as default on the subordinated debt of an institution
- Main idea: *Imply default probabilities and look at default correlations*

Modelling Approach: Risk

- **Systemic Losses**: Cumulative Losses for all financial institutions in case of distress ⏩ appx
- **Systemic Risk = Expected Shortfall**:
  - Average loss in 1% of the worst possible outcomes
- Marginal Expected Shortfall (MES):
  - Average loss from the institution, *given that the system is in 1% of the worst possible outcomes*
  - *Summation property*: Weighted MESs add up to the system's total ES ⏩ appx
- Risk Attribution: Percentage Contribution to Systemic Risk (PCtoES)

Modelling Approach: Default Correlations

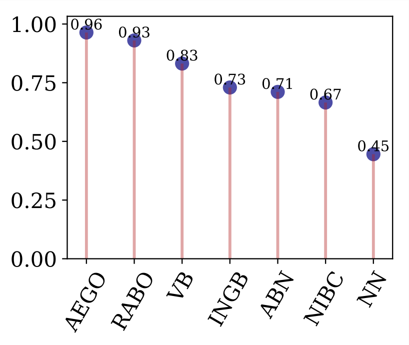
- Imply PDs from CDS data ⏩ appx $\rightarrow$ Assume Merton-type structural credit model ⏩ appx $\rightarrow$ Imply asset correlations through transformed changes in PDs ⏩ appx $\rightarrow$ Use asset correlations to fit a latent factor model ⏩ appx
- Simulate factors $\rightarrow$ Simulate Defaults and Recovery Rates ⏩ appx $\rightarrow$ Simulate bank and systemic losses $\rightarrow$ Attribute tail risk across all institutions $\rightarrow$ Rank by contribution to systemic risk.

Dataset

- CDS prices for subordinated debt
- Balance Sheet data (Liabilities and structure of the liabilities)
- Institutions
  - 5 Banks (ING Bank, ABN, Rabo, NIBC, Vb),
  - 2 Insurers (NN, Aegon)
- Time period: Sept-2019 to Sept, 2021; Also, overlapping period backtest: 2012 to 2021

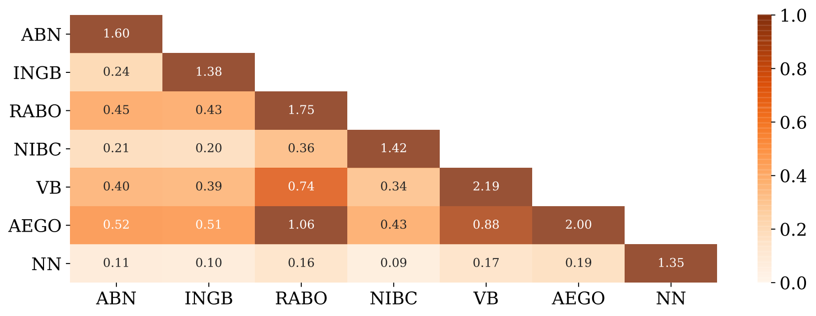
Results: Factor Loadings

Figure 1: Common Factor Loadings



Note. This figure shows the estimated exposure (loading) of each institution to the common latent factor.

Figure 2: Default Probability Matrix



(a) Joint Probability of Default

Note: This set of charts shows the probability that two institutions may default together over a one year horizon.

Results: Risk Rankings

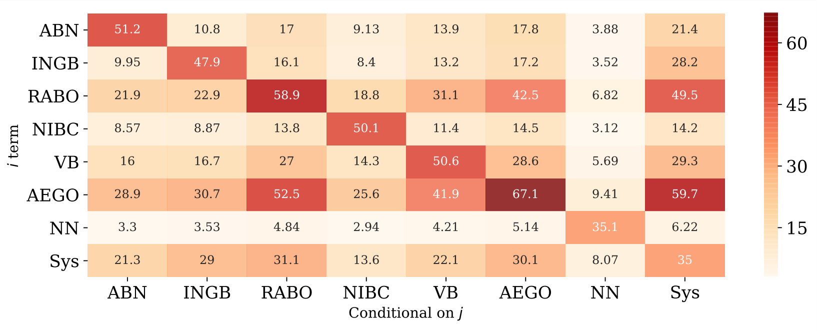
Table 1: Systemic Risk Statistics

	EL		w		ES99		MES99		PC to ES99	
ABN	0.73	(4)	14.67	(4)	51.21	(3)	21.38	(5)	8.95	(4)
INGB	0.60	(6)	34.57	(1)	47.87	(6)	28.24	(4)	27.86	(2)
RABO	0.97	(2)	23.24	(2)	58.88	(2)	49.45	(2)	32.80	(1)
NIBC	0.65	(5)	0.73	(7)	50.07	(5)	14.22	(6)	0.30	(7)
VB	0.94	(3)	2.50	(6)	50.56	(4)	29.33	(3)	2.09	(5)
AEGO	1.29	(1)	15.54	(3)	67.15	(1)	59.65	(1)	26.46	(3)
NN	0.47	(7)	8.75	(5)	35.09	(7)	6.22	(7)	1.55	(6)
System	0.81		100.00		35.05		35.05		100.00	

Note. This table shows the Expected Loss, Liability Weight, ES, MES, and Percentage Contribution to ES statistics. *All statistics are expressed as percent of liabilities of the company.* The numbers in the brackets provide the ranking relative to the group.

Results: Network ES

Figure 3: Network Expected Losses, $q = .99$



Note: These set of charts illustrate the network effects of tail losses. The chart shows the expected loss of the i entry, conditional on the j entry. Loss measured as percent of outstanding liabilities.

Policy Relevance of the Systemic Ranking

- Current policy frameworks on systemic buffers: GSIB (Global), O-SII (EU-wide, set by the national regulators under EBA guidance)
- Largely heuristic approaches
  - Rank institutions on several criteria: size, importance, complexity, interconnectedness
  - Average of all rankings
  - Bucket banks according to overall ranking and set additional risk buffers discretionary based on that
- O-SII buffers in the Netherlands for 2021: ING Bank (2.5%), Rabo (2%), ABN (1.5%), Volksbank (1%).
- Matches ranking by size (w_i), but not by *PC* to *ES*, where Rabo is before ING Bank

Room for future research

- Expand the universe of institutions (especially international linkages)
- Examine institutional characteristics that associate with high systemic risk
- Develop the current model into a comprehensive framework for setting systemic buffers to replace/enhance the current *ad hoc* approach
- Look into additional modeling features
    - Non-linear dependency + Network effects and contagion

Summary of findings

- *PC* to *ES* provides theoretically justified blending of risk, interdependence, and size; unlike current O-SII approaches
- Market-based measures of systemic risk could complement regulatory systemic rankings
- Could serve as a tool to explore risk dependencies between insurers and banks. Not covered well under current regulatory frameworks

Q & A

Any questions or comments?

Underlying Structural Model

- Market Value of Assets:

$$d \ln V_{i,t} = rdt + \sigma_{v,i} dW_{i,t} \tag{1}$$

- Co-variation through latent factors

$$dW_{i,t} = A_i M_t + \sqrt{1 - A_i A_i'} Z_{i,t} \tag{2}$$

M_t: Vector of common factors; Z_i: idiosyncratic factor; A_i: factor loadings, $A_i A_i' \leq 1$

- Default threshold (Distance-to-Default)

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

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Collateral Process

- Model the value of collateral backing liabilities as:

$$d\ lnC_{i,t} = \sigma_c dW^c_{i,t} \tag{3}$$

- where the collateral is defined through the factor model

$$dW^c_i = A_i M_t + \sqrt{1 - A_i A_i'} Z^c_{i,t} \tag{4}$$

- This generates dependent losses $(1 - RR_{i,t})$

$$RR_{i,t} = \mu_{c,i} \min(1, C_{i,t}) \tag{5}$$

  RR_i: Recovery Rate

- σ_c matched to VSTOXX index (implied vola of the Euro Stoxx 50 index): generates time variation to accounts for risk appetite; $\mu_{c,i}$ matched to ERR_i;

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Appendix: PD in Merton's model

- Fixed Default Barrier

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

- PD defined by Distance to Default (DD)

$$
PD_{i,t} = \Phi(-DD_{i,t}) \tag{6}
$$

with

$$
DD_{i,t} = \frac{\ln \frac{V_{i,t}}{D_i} + \left(r - \frac{\sigma_{v,i}^2}{2}\right)\Delta t}{\sigma_{v,i}\sqrt{\Delta t}}
$$

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Asset Correlations in Merton's model

- Asset correlations btw institution linked to changes in PDs

$$
\begin{aligned}
\rho_{ij} &= Corr(\Delta \ln V_{i,t}, \Delta \ln V_{j,t}) \\
&= Corr(\sigma_{v,i} \Delta DD_{i,t}, \sigma_{v,j} \Delta DD_{j,t}) \\
&= Corr\left(\Delta \Phi^{-1}(PD_{i,t}), \Delta \Phi^{-1}(PD_{j,t})\right)
\end{aligned}
$$

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Latent Factor Estimation

- Estimate factor loadings based on the correlations of the transformed PDs

$$\min_{\hat{A}_1,\ldots,\hat{A}_n} \sum_{i=2}^{N} \sum_{j=1}^{N} (\rho_{ij} - \hat{A}_i \hat{A}_j')^2 \tag{7}$$

- Efficient minimization algorithm using principal components iteratively, *Andersen and Basu [2003]*
- The factor captures the common variation of the transformed PDs

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Appendix: Extract PDs from CDS prices

- CDS valuation, Duffie [1999]: CDS_t is set to equalize the expected present value of the two swap legs.

$$\underbrace{CDS_t \int_t^{t+T} e^{-r_\tau \tau} \Gamma_\tau d\tau}_{\text{PV of CDS premia}} = \underbrace{(1 - ERR_t) \int_t^{t+T} e^{-r_\tau \tau} q_\tau d\tau}_{\text{PV of protection payment}} \tag{8}$$

  Γ_τ: survival probability; r_τ: interest rate; ERR: Expected Recovery Rate; q_τ: hazard rate (ann. default probability, conditional on no default previously)
- Assume fixed: ERR (here only), interest rate, hazard rate
- ERR calibrated based on liabilities structure (80% on deposits/policy insurance; 40% on other)
- Set $PD_t = q_t$ in (6)

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Losses of the systemic portfolio

- Systemic losses over the next year

$$L_{sys} = \sum_{i=1}^{n} w_i L_i \qquad (9)$$
$$L_i = \mathbf{1}_{d_i}(1 - RR_i)$$

$\mathbf{1}_{d_i}$: Default indicator (implied from the CDS rates and the Merton Model); L_i: loss by institution i; w_i: liability weight; RR: Recovery Rate

- Simulate 1_{d_i} and RR_i to evaluate systemic losses and contributions

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- Expected Shortfall

$$ES_i = E(L_i | L_i \geq VaR_i)$$

- Marginal Expected Shortfall:

$$MES_{i|sys} = E\left(L_i | L_{sys} \geq VaR_{sys}\right)$$

- Percentage Contribution to ES:

$$PC \text{ to } ES_i = \frac{w_i MES_i}{ES_{sys}} \tag{10}$$

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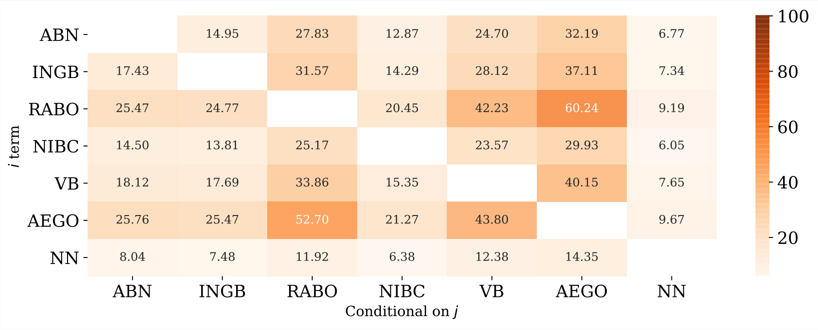
Results: Conditional

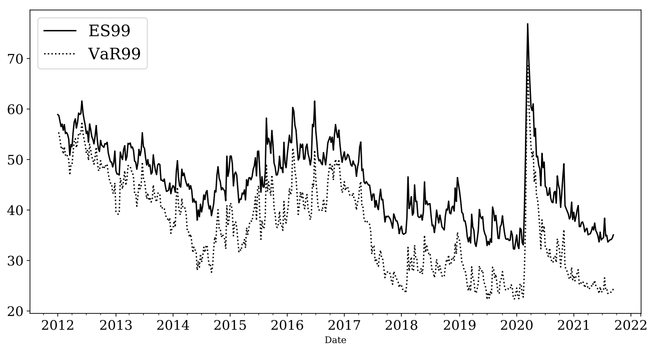
Figure 4: Default Probability Matrix



(a) Conditional Probability of Default

Note: This set of charts shows the probability that institution *i* may default, conditional on *j* being in default.

Figure 5: Systemic Risk (ES, VaR) Over Time



Note. This plot shows the tail risk of the systemic portfolio quantified by the *ES* and *VaR*.

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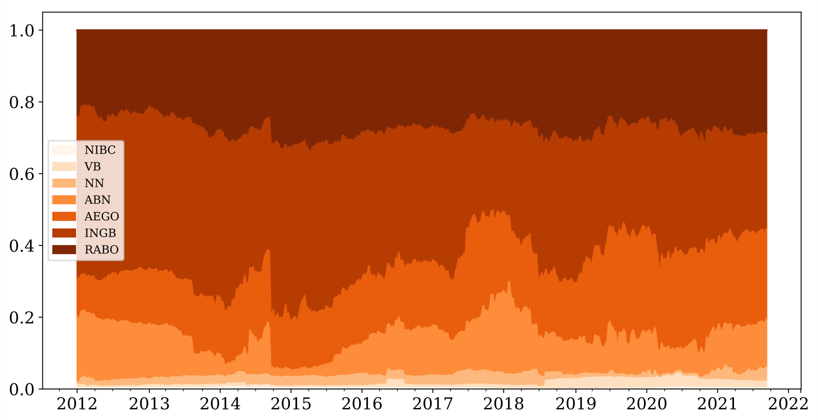
Appendix: MES

Figure 6: 99% MES (PCtoES) Over Time



This figure shows the MES vs. the ES at $q = .99\%$ respectively for each company. The *MES* of the institutions sums up to the total *ES* of the system.

Appendix: Robustness to other Systemic Measures

Table 2: Systemic Rankings Comparison

	MES	*ECoVaR*	*VI*
MES			
ECoVaR	0.64		
VI	0.96	0.68	

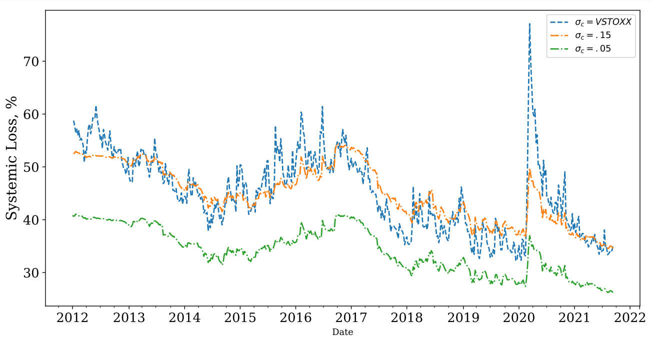
(a) Rank Correlations

	w	PC to ES	$w \cdot ECoVaR$	$w \cdot VI$
w				
PC to ES	0.93			
$w \cdot ECoVaR$	1.00	0.93		
$w \cdot VI$	0.96	0.96	0.96	

(b) Rank Correlations, Weighted Measures

Appendix: Robustness to σ_c

Figure 7: Expected Shortfall of the Systemic Portfolio



Note. This figure shows ES for the system calculated based on two assumption: σ_c is scaled by the implied volatility of the VSTOXX index, and σ_c is fixed to 20%. Evaluated at .95 confidence level.