Quantifying Systemic Risk in the Presence of Unlisted Banks

Application to the European Financial Sector

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1. Motivation

Motivation

- Macroprudential policy widely acknowledged to be of prime importance but implementation tends to be *ad hoc*
- A large gap between *academic* and *policy* approaches to systemic risk
  - Academic focus on implying (tail) dependencies from asset prices (Acharya eA, 2017; Adrian/Brunnermeier, 2016; ...)
  - Regulators focus on balance sheet/transaction data and regulatory scores (O-SII, G-SII scoring)

Motivation

- Key challenge: many European banks are not publicly traded on the equity market
- ... but they are traded on the Credit Default Swaps (CDS) market
- Methodology is still general and could be applied to non-market data

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;

Related Literature

- 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))
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Why use CDS prices?

- CDS: insurance derivative contract (OTC) on default of an underlying
- Linked directly to the default risks of the company
  - More liquid and with fewer trading frictions than the corporate bond market
  - An edge over credit rating agencies
- Standardized T&Cs (maturities, the definition of a credit event, etc.)
- Some evidence CDS prices may lead the equity markets in price discovery *Acharya & Johnson [2005]*

CDS prices

- CDS prices on banks' subordinate debt: less likely to be bailed out in default
- Contract counterparty risk eliminated for centrally cleared contracts
- Less liquid than the equity market, but illiquidity often indicator of higher credit risk (Brunnermeier/Pedersen, 2009; Diamond/Rajan, 2011)
- CDS Market transparency, liquidity and resilience increased substantially since the GFC (BIS, 2018)
- Alternative sources of distress probabilities of default exist...
    - ... but how predictive are they really?

2. Model

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:
    1. Imply default probabilities from CDS spreads
    2. Evaluate default correlations from CDS co-movements over time
    3. Evaluate the cumulative potential losses withing the system

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 cumulative normal distribution.

Default dependencies through latent factors (Gaussian Copula)

$$U_i = A_i M + \sqrt{1 - A_i A_i'} Z_i \tag{2}$$

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

Allows the Estimation of Banks' Asset Correlations

- The ⏩ Merton model has important implications *on the implied asset correlations*:

$$
\begin{aligned}
a_{ij} &\equiv \mathbb{Corr}(U_i, U_j) \\
&= \mathbb{Corr}(\Delta\Phi^{-1}(-PD_{i,t}), \Delta\Phi^{-1}(-PD_{i,t}))
\end{aligned}
$$

- Determine factor exposures ρ_i to closely ⏩ match these implied correlations.
- Imply time series $PD_{i,t}$ ⏩ from the CDS data
- Once the exposures are fixed, the latent varables U_i can be simulated
- Default threshold is fixed by the PD-implied Distance-to-Default $\implies$ Defaults can be simulated in a multi-variate space

Quantifying Systemic Risk: (Marginal) Expected Shortfall

- The financial system can be seen as a portfolio of long loan positions
- Formally, define (correlated credit losses) as

$$L_i = \mathbb{1}_i LGD_i; \quad L_{sys} = \sum_{i=1}^{N} w_i L_i \tag{3}$$

- Define Expected Systemic Shortfall and Marginal Expected Shortfall [Acharya eA, 2017; Huang eA 2012]:

$$\begin{aligned} MES_i &= \mathbb{E}\left(L_i \middle| L_{sys} > VaR_{sys}\right) \\ ESS &= \mathbb{E}\left(L_{sys} \middle| L_{sys} > VaR_{sys}\right) \end{aligned} \tag{4}$$

- Percentage Contribution to ESS:

$$PC \text{ to } ESS_i = \frac{w_i MES_i}{ESS} \tag{5}$$

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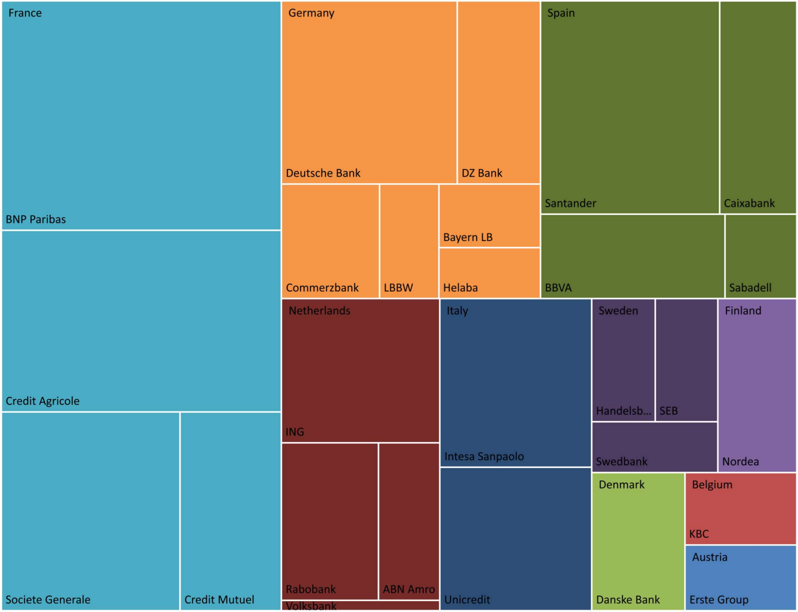
3. Empirical Application

Analysis Dataset

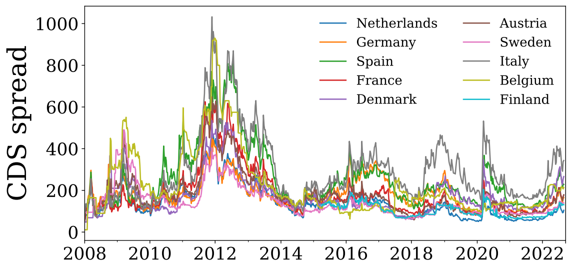
- Universe of 27 large European banks (O-SII and G-SII).
- Evaluation date: Aug, 29, 2022
- Correlation time window: 3 years
- Dataset: CDS spreads on subordinate debt; Balance sheet liability sizes

Relative Liability Size



CDS Prices

Figure 1: Median Rates per Country (bps)

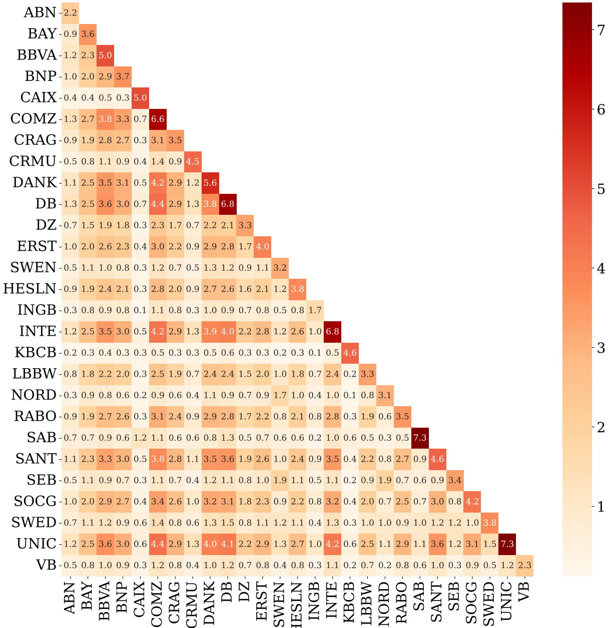


- Using CDS data to imply risk
  - Levels of the CDS rate speak about the market view on the credit-worthiness of the institution
  - Co-movements in CDS prices speak about the tendency of banks to be exposed to the same risk drivers
- Liability sizes speak about the Exposure at Default (EAD)

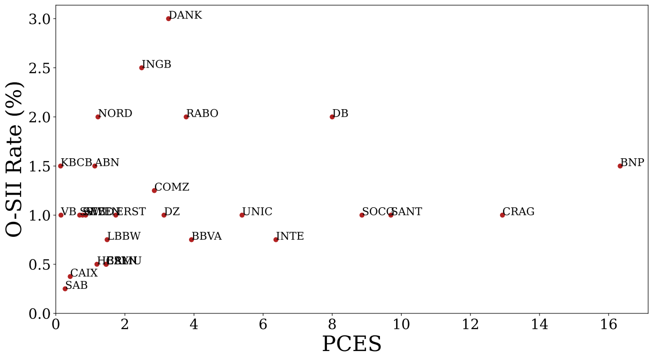
ii. Estimated Factor Loadings

		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)

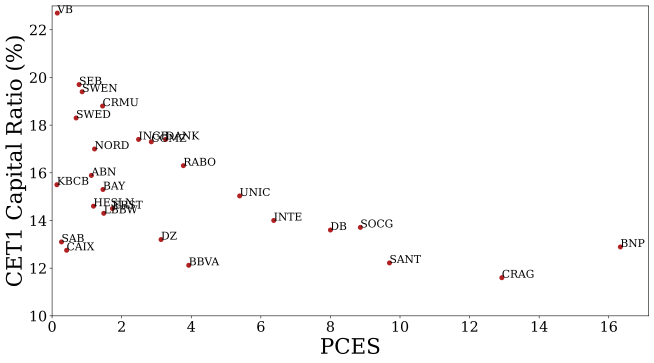
Joint PDs


ABN 2.2
BAY 0.9 3.6
BBVA 1.2 2.3 5.0
BNP 1.0 2.0 2.9 3.7
CAIX 0.4 0.4 0.5 0.3 5.0
COMZ 1.3 2.7 3.8 3.3 0.7 6.6
CRAG 0.9 1.9 2.8 2.7 0.3 3.1 3.5
CRMU 0.5 0.8 1.1 0.9 0.4 1.4 0.9 4.5
DANK 1.1 2.5 3.5 3.1 0.5 4.2 2.9 1.2 5.6
DB 1.3 2.5 3.6 3.0 0.7 4.4 2.9 1.3 3.8 6.8
DZ 0.7 1.5 1.9 1.8 0.3 2.3 1.7 0.7 2.2 2.1 3.3
ERST 1.0 2.0 2.6 2.3 0.4 3.0 2.2 0.9 2.9 2.8 1.7 4.0
SWEN 0.5 1.1 1.0 0.8 0.3 1.2 0.7 0.5 1.3 1.2 0.9 1.1 3.2
HESLN 0.9 1.9 2.4 2.1 0.3 2.8 2.0 0.9 2.7 2.6 1.6 2.1 1.2 3.8
INGB 0.3 0.8 0.9 0.8 0.1 1.1 0.8 0.3 1.0 0.9 0.7 0.8 0.5 0.8 1.7
INTE 1.2 2.5 3.5 3.0 0.5 4.2 2.9 1.3 3.9 4.0 2.2 2.8 1.2 2.6 1.0 6.8
KBCB 0.2 0.3 0.4 0.3 0.3 0.5 0.3 0.3 0.5 0.6 0.3 0.3 0.2 0.3 0.1 0.5 4.6
LBBW 0.8 1.8 2.2 2.0 0.3 2.5 1.9 0.7 2.4 2.4 1.5 2.0 1.0 1.8 0.7 2.4 0.2 3.3
NORD 0.3 0.9 0.8 0.6 0.2 0.9 0.6 0.4 1.1 0.9 0.7 0.9 1.7 1.0 0.4 1.0 0.1 0.8 3.1
RABO 0.9 1.9 2.7 2.6 0.3 3.1 2.4 0.9 2.9 2.8 1.7 2.2 0.8 2.1 0.8 2.8 0.3 1.9 0.6 3.5
SAB 0.7 0.7 0.9 0.6 1.2 1.1 0.6 0.6 0.8 1.3 0.5 0.7 0.6 0.6 0.2 1.0 0.6 0.5 0.3 0.5 7.3
SANT 1.1 2.3 3.3 3.0 0.5 3.8 2.8 1.1 3.5 3.6 1.9 2.6 1.0 2.4 0.9 3.5 0.4 2.2 0.8 2.7 0.9 4.6
SEB 0.5 1.1 0.9 0.7 0.3 1.1 0.7 0.4 1.2 1.1 0.8 1.0 1.9 1.1 0.5 1.1 0.2 0.9 1.9 0.7 0.6 0.9 3.4
SOCG 1.0 2.0 2.9 2.7 0.4 3.4 2.6 1.0 3.2 3.1 1.8 2.3 0.9 2.2 0.8 3.2 0.4 2.0 0.7 2.5 0.7 3.0 0.8 4.2
SWED 0.7 1.1 1.2 0.9 0.6 1.4 0.8 0.6 1.3 1.5 0.8 1.1 1.2 1.1 0.4 1.3 0.3 1.0 1.0 0.9 1.0 1.2 1.2 1.0 3.8
UNIC 1.2 2.5 3.6 3.0 0.6 4.4 2.9 1.3 4.0 4.1 2.2 2.9 1.3 2.7 1.0 4.2 0.6 2.5 1.1 2.9 1.1 3.6 1.2 3.1 1.5 7.3
VB 0.5 0.8 1.0 0.9 0.3 1.2 0.8 0.4 1.0 1.2 0.7 0.8 0.4 0.8 0.3 1.1 0.2 0.7 0.2 0.8 0.6 1.0 0.3 0.9 0.5 1.2 2.3
ABN BAY BBVA BNP CAIX COMZ CRAG CRMU DANK DB DZ ERST SWEN HESLN INGB INTE KBCB LBBW NORD RABO SAB SANT SEB SOCG SWED UNIC VB
7
6
5
4
3
2
1

Risk Contribution vs. O-SII Buffers

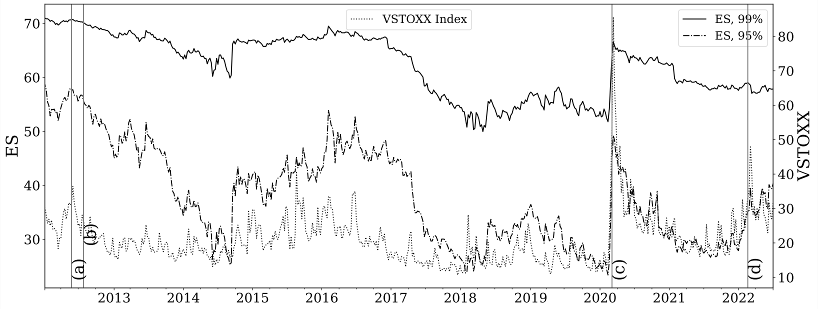


Risk Contribution vs. Total CET1 Buffers



Aggregate Systemic Risk Contributions

Figure 4: Expected Systemic Shortfall vs. VSTOXX



(a) Draghi's "courageous leap" speech to save the euro; (b) Draghi's "whatever it takes speech"; (c) the first Covid lock-downs in Europe (in Italy); (d) the Russian invasion in Ukraine.

Non-linear Factor Extensions

- The Student-t model

$$Ui = \sqrt{h(F)}\left(AiM + \sqrt{1 - AiAi'}Z_i\right) \tag{6}$$

where $h(F) = \frac{\nu}{F}$ with $F \sim \chi^2(\nu)$.

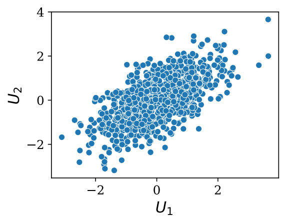
- The Skewed-t model

$$Ui = \sqrt{\frac{\nu}{F}}\left(\delta G + AiM + \sqrt{1 - AiAi'}Z_i\right) \tag{7}$$

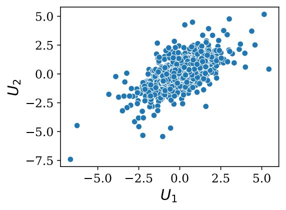
where $G \sim TN\left(-\sqrt{\frac{2}{\pi}}, 1\right)$, with $TN(\mu, \sigma)$ is a normal distribution truncated left at $-\sqrt{\frac{2}{\pi}}$.

Non-linear Factor Extensions

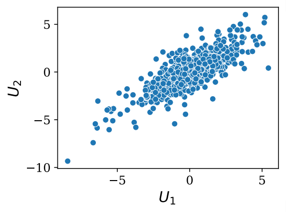
Figure 5: Simulated Factor Copula



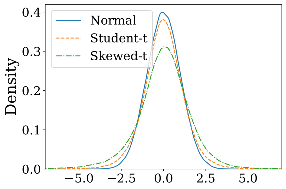
(a) Gaussian



(b) Student-t



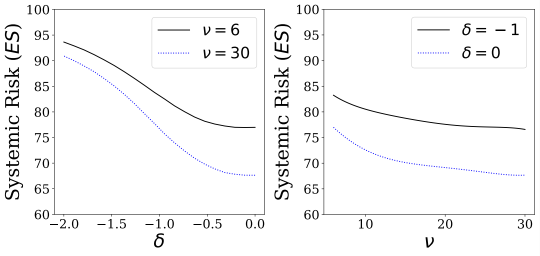
(c) Skewed-t



(d) Marginal Distribution

Non-linear Factor Extensions

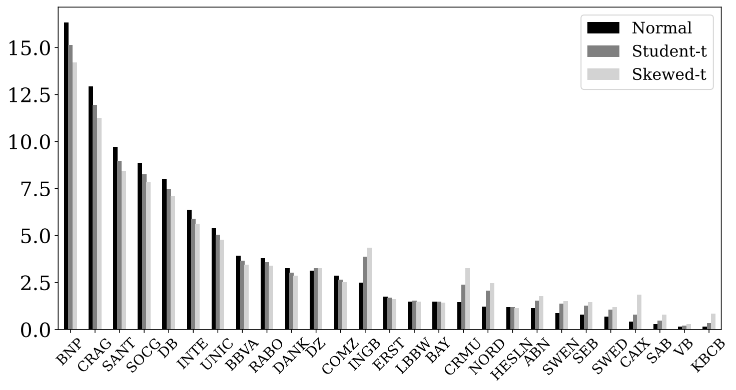
Figure 7: Aggregate Tail Risk, Model Comparison



(a) Skewed-t **(b)** Skewed-t

Non-linear Factor Extensions

Figure 9: Model Comparison PCES



Summary of findings

- *PC* to *ES* provides theoretically justified blending of risk, interdependence, and size; unlike current O-SII approaches
- Our market-based evaluation based shows large discrepancy between larger banks' capitalization and their contribution to EU-wide systemic risk
- Market-based measures of systemic risk could complement regulatory systemic rankings
- Challenges of the current O-SII methodology
  - Evidence that large banks may window dress statistics relevant for their O-SII scores
  - Significant heterogeneity across EU countries in mapping from O-SII scores to O-SII buffers
  - Systemic evaluation w.r.t local economy rather than EU-wide
- Results robust to adding non-linear factors in the Copula specification to capture asset skewness and tail-fatness

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Appendix

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.

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

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 $PD_t = q_t$ for each bank i back

Collateral Process

- Model the value of collateral backing liabilities as:

$$d\ lnC_{i,t} = \sigma_c dW^c_{i,t} \tag{9}$$

- where the collateral is defined through the factor model

$$dW^c_i = A_i M_t + \sqrt{1 - A_i A'_i} Z^c_{i,t} \tag{10}$$

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

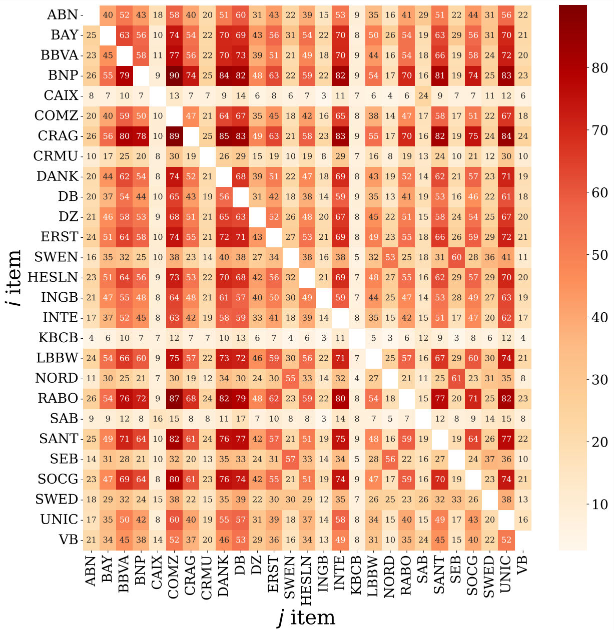
$$RR_{i,t} = \mu_{c,i} \min(1, C_{i,t}) \tag{11}$$

  RR$_i$: Recovery Rate

- σ_c matched to generate reasonable variance of the RRs; $\mu_{c,i}$ matched a reasonable ERR;

back

Results: Conditional



Relation to a Structural Credit Model

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

$$d \ln V_{i,t} = r dt + \sigma_i dW_{i,t} \tag{12}$$

where $V_{i,t}$ is the market value of the bank's risk-weighted assets; σ_i is their st.dev.; r is the risk-free rate; $dW_{i,t}$ is a Brownian Motion.

- Default occurs if assets fall below the face value of debt at time T

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

- Distance-to-Default (DD):

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

▸▸ back

Estimation of Factor Exposures

Estimate all ρ_i, ρ_j relative to a target correlation matrix

$$\min_{\rho_i,\ldots,\rho_j} \sum_{i=2}^{N} \sum_{j=1}^{N} (a_{ij} - \rho_i \rho_j')^2 \tag{13}$$

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

back