

Econophysics V: Credit Risk

Thomas Guhr

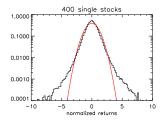
Let's Face Chaos through Nonlinear Dynamics, Maribor 2011

Outline

Outline

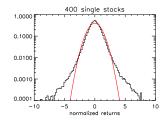
- Introduction
- Market risk versus Credit risk
- Reduced form models versus Structural models
- Loss distribution
- ▶ Numerical simulations and Random matrix approach
- Conclusions: general, present credit crisis

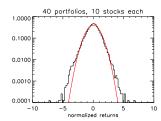
Introduction



empirical distribution of normalized returns (400 stocks)

Diversification in a stock portfolio, no correlations

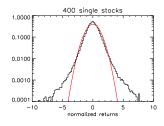


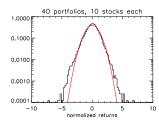


- empirical distribution of normalized returns (400 stocks)
- portfolio: superposition of stocks

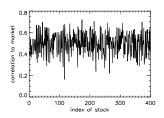
Model

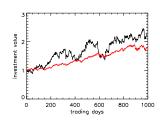
Diversification in a stock portfolio, no correlations





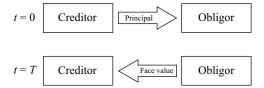
- empirical distribution of normalized returns (400 stocks)
- portfolio: superposition of stocks
- risk reduction by diversification (no correlations yet!): returns are more normally distributed, market risk reduced by approx. 50 percent





- stocks highly correlated to overall market
- risk reduction by diversification (with correlations): unsystematic risk can be removed, systematic risk (overall market) remains

What's different for credits?



- principal: borrowed amount
- ▶ face value F: borrowed amount + interest + risk compensation
- credit contract with simplest cash-flow

- default occurs if the obligor fails to repay
 - \Rightarrow loss between 0 and face value F
- possible losses have to be priced into credit contract
- correlations are important to evaluate the risk of a credit portfolio

Defaults and Losses

- default occurs if the obligor fails to repay
 - \Rightarrow loss between 0 and face value F
- possible losses have to be priced into credit contract
- correlations are important to evaluate the risk of a credit portfolio
- statistical modeling needed
- reduced form models versus structural models

Reduced form models

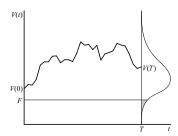
- macroscopic approach
- different aspects (observables) are modelled independently
 - default events as point process
 - recovery rates modelled independently
 - correlations e.g. as network model

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Reduced form models

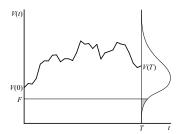
- macroscopic approach
- different aspects (observables) are modelled independently
 - default events as point process
 - recovery rates modelled independently
 - correlations e.g. as network model
- goal: describe empirical statistical properties and market prices for credit products by callibrating with credit products
- problem: the market may be wrong!

Structural models



- ► microscopic approach
- ▶ dynamical description of risk factors $V_k(t)$, k = 1, ..., K
- ▶ default occurs if asset value $V_k(T)$ falls below face value F_k
- ▶ then the (normalized) loss is $L_k = \frac{F_k V_k(T)}{F_k}$

Structural models



- ► microscopic approach
- dynamical description of risk factors $V_k(t)$, k = 1, ..., K
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- ▶ then the (normalized) loss is $L_k = \frac{F_k V_k(T)}{F_k}$
- e.g. credits with stock portfolio or houses as securities

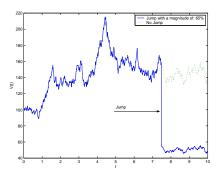
A model with jumps and correlations

$$\frac{\mathrm{d}V_k}{V_k} = \mu_k \,\mathrm{d}t + \sigma_k \varepsilon_k \sqrt{\mathrm{d}t} + \mathrm{d}J_k$$

Geometric Brownian motion with

- deterministic term $\mu_k dt$
- diffusion term $\sigma_k \varepsilon_k \sqrt{\mathrm{d}t}$
- **b** jump term dJ_k , governed by a Poisson process
- K risk elements $V_k = V_k(t), k = 1, ..., K$

Jump process and return distribution



jumps yield heavy tails in the price and return distributions

Jumps as Poisson process

- lacktriangle we model jumps by Poisson process with intensity λ
- probability for n jumps between 0 and t:

$$p_n(t) = \frac{(\lambda t)^n}{n!} \exp(-\lambda t)$$

- ▶ largest negative jump: -100% of V(t)
- ightharpoonup we choose shifted log-normal distribution for jump size Λ

$$ln(\Lambda + 1) \sim N(\mu_J + 1, \sigma_J)$$

Correlate K risk elements: one-factor model

- \triangleright ε_k is random variable for company k
- lacksquare η is common random variable within one branch
- correlated diffusion, uncorrelated jumps:

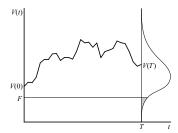
$$\frac{\mathrm{d}V_k}{V_k} = \mu_k \,\mathrm{d}t + \left(\sqrt{1-c}\,\varepsilon_k + \sqrt{c}\,\eta\right)\sigma_k\sqrt{\mathrm{d}t} + \mathrm{d}J_k$$

add influence of market as a whole

$$\frac{\mathrm{d}V_k}{V_k} = \mu_k \,\mathrm{d}t + \left(\sqrt{1-c}\,\varepsilon_k + \sqrt{c}\,\eta\right)\sigma_k\sqrt{\mathrm{d}t} + \mathrm{d}J_k + \mathrm{d}J_\mathrm{m}$$

Loss distribution

Individual losses



- ▶ normalized loss: $L_k = \frac{F_k V_k(T)}{F_k}$
- default probability: $P_{D,k} = \int_{0}^{F_k} p_k(V_k(T)) dV_k(T)$
- truncate distribution $p_k(V_k(T)) \rightarrow p_k(L_k)$

Default event

default indicator

$$I_k = \left\{ egin{array}{ll} 1 & , & \mbox{if} & V_k(T) < F_k & \mbox{(default)} \\ 0 & , & \mbox{if} & V_k(T) > F_k & \mbox{(no default)} \end{array}
ight.$$

indicator distribution

$$\tilde{p}_k(I_k) = (1 - P_{D,k})\delta(I_k) + P_{D,k}\delta(I_k - 1)$$

Outline

Portfolio loss distribution

- ▶ portfolio loss: $L \frac{1}{K} \sum_{k=1}^{K} L_k I_k$
- loss distribution

$$p(L) = \int_{-\infty}^{+\infty} dI_1 \tilde{p}_1(I_1) \cdots \int_{-\infty}^{+\infty} dI_K \tilde{p}_K(I_K) \int_0^1 dL_1 p_1(L_1) \cdots \int_0^1 dL_K p_K(L_K)$$
$$\times \delta \left(L - \frac{1}{K} \sum_{k=1}^K L_k I_k \right)$$

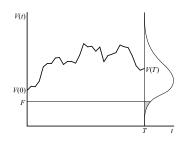
▶ special case K = 1 yields: $p(L) = (1 - P_{D,1}) \delta(L) + P_{D,1} p_1(L)$

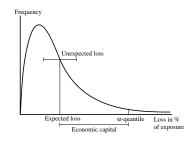
Real portfolios comprise several hundred or more individual contracts \longrightarrow K is large.

Central Limit Theorem: For very large K, portfolio loss distribution p(L) must become Gaussian.

Question: how large is "very large"?

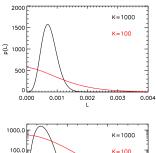
Distribution of credit losses

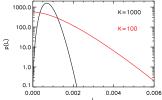




- portfolio loss is arithmetic mean of individual losses
- mean of loss distribution is called expected loss (EL)
- standard deviation is called unexpected loss (UL)
- kurtosis excess (KE) to measure heavy tails: $\gamma_2 = \mu_4/\mu_2^2 3$

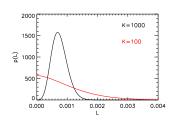
- homogenous portfolio
- analytical approximations
- check Monte-Carlo results

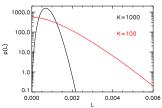




Simplified model — no jumps, no correlations

- homogenous portfolio
- analytical approximations
- check Monte-Carlo results
- slow convergence to Gaussian for large portfolio
- ► K = 1000 not yet Gaussian CIT-limit
- kurtosis excess of uncorrelated portfolios scales as 1/K

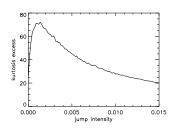


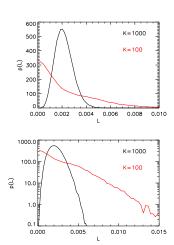


Numerical simulations

Numerical simulations: influence of jumps, no correlations

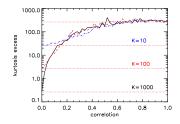
- diffusion and jumps compete
- KE has maximum, but scales as 1/K

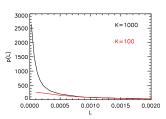


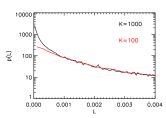


Numerical simulations: influence of correlations, no jumps

- correlation coefficientc = 0.5
- transition from uncorrelated to fully correlated



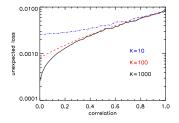


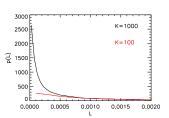


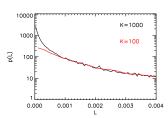
$$c = 0.5$$

Numerical simulations: influence of correlations, no jumps

- standard deviation decreases
- bad measure for credit risk!
- diversification does not reduce the risk







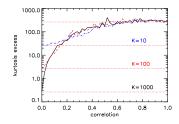
$$c = 0.5$$

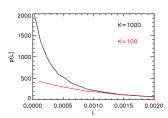
Numerical simulations: influence of correlations, no jumps

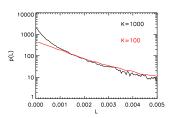
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Numerical simulations

- correlation coefficient c = 0.2
- transition from uncorrelated to fully correlated



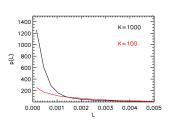


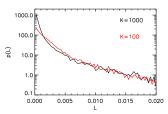


$$c = 0.2$$

Numerical simulations: jumps and correlations

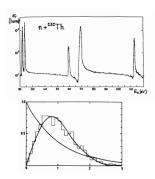
- correlated jump-diffusion
- one-branch correlations
- c = 0.5
- tail behavior stays similar with increasing K





Random matrix approach

Quantum Chaos



statistical nuclear physics

universal in a huge variety of systems: nuclei, atoms, molecules, disordered systems, lattice gauge quantum chromodynamics, elasticity, electrodynamics

 $\hbox{``second ergodicity'': spectral average} = \hbox{ensemble average}$

→ random matrix theory

Price distribution at maturity

Brownian motion, $V = (V_1(T), \dots, V_K(T))$, price distribution

$$p^{(\mathrm{mv})}(V,\Sigma) = \frac{1}{\sqrt{2\pi T}^K} \frac{1}{\sqrt{\det \Sigma}} \exp\left(-\frac{1}{2T} (V - \mu T)^{\dagger} \Sigma^{-1} (V - \mu T)\right)$$

covariance matrix $\Sigma = \sigma W W^{\dagger} \sigma$ with fixed $\sigma = \mathsf{diag}\left(\sigma_{1}, \ldots, \sigma_{K}\right)$

assume Gaussian distributed correlation matrix WW^{\dagger} with W rectangular real $K \times N$, variance 1/N

$$p^{(\text{corr})}(W) = \sqrt{\frac{N}{2\pi}}^{KN} \exp\left(-\frac{N}{2} \text{tr } W^{\dagger}W\right)$$

average correlation is zero

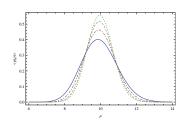
Average price distribution

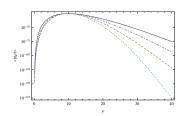
$$\langle \rho^{(\mathrm{mv})}(\rho) \rangle = \sqrt{\frac{N}{2\pi T}}^{\kappa} \frac{2^{1-\frac{N}{2}}}{\Gamma(N/2)} \rho^{\frac{N-\kappa-1}{2}} \sqrt{\frac{N}{T}}^{\frac{N-\kappa}{2}} \mathcal{K}_{\frac{N-\kappa}{2}} \left(\rho \sqrt{\frac{N}{T}} \right)$$

with hyperradius
$$\rho = \sqrt{\sum_{k=1}^{K} \frac{V_k^2(T)}{\sigma_k^2}}$$

easily transferred to geometric Brownian motion

Heavy tailed average distribution



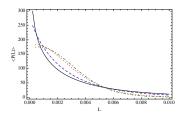


$$K = 50 \text{ and } N = K, 2K, 5K, 30K$$

N smaller \longrightarrow stronger correlated \longrightarrow heavier tails

Loss distribution — varying correlation strength

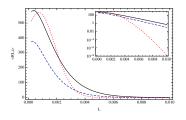
integrate out risk elements, semi-analytical result

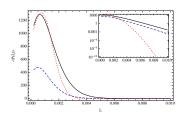


homogeneous portfolio K = 10 and N = K, 2K, 10K, 30K

also here: stronger correlated \longrightarrow heavier tails

Loss distribution — varying portfilio sizes





homogeneous portfolios K = 50, 100, strongly correlated N = K

heavy tails robust!

General conclusions

- correlated jumps lead to extremely fat-tailed distribution
- \triangleright kurtosis excess (KE) scales as 1/K for uncorrelated portfolios
- ▶ KE does not scale down well for correlated portfolios, even for low correlation coefficients
- correlations of stocks to market movement typically between 0.4 and 0.6
- other scenarios: houses, cars, etc as security for credits
- ensemble average reveals generic features of loss distributions
- lower bound, because average correlation is zero

Conclusions in view of the present credit crisis

- credit contracts with high default probability,
 e.g. houses as securities
- credit institutes resold the risk of credit portfolios, grouped by credit rating
- ▶ lower ratings ⇒ higher risk and higher potential return
- problems:
 - rating agencies rated way too high
 - effect of correlations underestimated
 - benefit of diversification overestimated

R. Schäfer, M. Sjölin, A. Sundin, M. Wolanski and T. Guhr, Credit Risk - A Structural Model with Jumps and Correlations, Physica A383 (2007) 533

M.C. Münnix, R. Schäfer and T. Guhr, A Random Matrix Approach to Credit Risk, arXiv:1102.3900

both ranked for several months among the top—ten new credit risk papers on www.defaultrisk.com