

Growth in coupled multiplicative stochastic processes

International Workshop
The Physics Approach to Risk:
Agent-Based Models and Networks

Jan Lorenz

Chair of Systems Design

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Outline

- 1 Swiss COST P10 Project: Failure Risk Propagation in Economic and Supply Networks
- 2 Growth in Coupled Multiplicative Stochastic Processes

Failure Risk Propagation in Economic and Supply Networks¹

3 Parts:

- 1 Fragility dynamics with trend persistence
 - ▶ Result: Non-monotonous impact of link density
- 2 **Growth in coupled multiplicative stochastic processes**
- 3 Cascades in credit and supply networks
 - ▶ In preparation

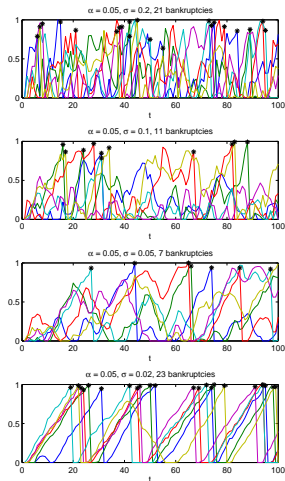
¹Chair of Systems Design (Prof. Schweitzer, Stefano Battiston) and Institute for Operations Research (Prof. Lüthi, Marco Laumanns), ETH Zurich

Less volatility, higher failure risk?²

- Fragility of n firms evolves as

$$\underbrace{\phi(t+1) = \phi(t)}_{\text{fragility}} + \underbrace{\sigma \xi(t)}_{\text{stochastic shocks}} + \underbrace{\alpha \text{sign}(\Delta \phi(t))}_{\text{trend reinforcing}}$$

- trend reinforcing $\nearrow \rightsquigarrow \nearrow \nearrow$, $\searrow \rightsquigarrow \searrow \searrow$
- reducing volatility σ
 - ▶ decreases stochastic shocks
→ less bankruptcies, BUT
 - ▶ reduces possibility to break bad trends →
more bankruptcies!
- Conclusion: We are safest with intermediate volatility



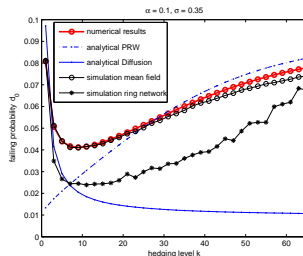
²Jan Lorenz, Stefano Battiston, Networks and Heterogeneous Media, 2008

Local optimum explained by stochastic process

- Scaling of displacement for Gaussian Random Walk (GRW) and Persistent Random Walk (PRW)

$$\phi(t+1) = \phi(t) + \underbrace{\sigma \xi(t)}_{\text{diffusive scaling}} + \underbrace{\alpha \text{trend}}_{\text{ballistic} \rightarrow \text{diffusive}}$$

- GRW dominates for $\frac{\alpha}{\sigma} \rightarrow 0$, PRW for $\frac{\alpha}{\sigma} \rightarrow \infty$



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Motivation

Growth is fundamental to economic (and other) development

- Many processes grow proportional to size (**multiplicative growth**)
 - ▶ invested money
 - ▶ knowledge or innovativeness
 - ▶ populations
- Growing entities exchange in a **linear input-output** manner
 - ▶ trade
 - ▶ exchange of knowledge

What is impact of combining the two on the **effective growth rate**?

In the following:

- 1 Take **knowledge** as proxy for the dynamic variable $x(t)$
- 2 Define simple **internal stochastic** multiplicative growth dynamics
- 3 Define simple linear input-output dynamics for a small **ensemble**
- 4 Find: Even when
 - ▶ internal dynamics lead to **extinction**
 - ▶ input-output is lossy and leads to **shrinking**

→ **The combination can imply growth**
- 5 Phase transitions positive/negative growth rates (**Risk of Extinction!**), regarding e.g.
 - ▶ number of firms
 - ▶ sharing rate

Multiplicative stochastic knowledge production

- The knowledge of a firm to be initially $x(0) = 1$
- There is a **positive random variable** for the growth rate η
- Dynamics take place in **discrete time** as

$$x(t + 1) = \eta(t)x(t)$$

- As example p **success rate**, r **loss rate**, b **gain rate**,

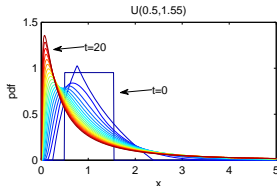
$$\eta_{r,b,p}(t) = \begin{cases} 1 + b & \text{with probability } p, \\ 1 - r & \text{with probability } 1 - p. \end{cases}$$

- **Let's assume:** $\langle \eta_{r,b,p} \rangle > 1$ because of hard work/knowledge management/optimism

Multiplicative stochastic process $x(t) = \eta(t)x(t)$

- In general (for $\log \eta$ with finite variance)
 - ▶ The central limit theorem for $\log x(t+1) = \log \eta(t) + \log x(t)$ implies for large t that $x(t)$ is close to **log-normal** distributed, with cdf and pdf

$$F_{x(t)}(x) = \frac{1}{2} + \frac{1}{2} \operatorname{erf} \left[\frac{\log(x) - t\mu_{\log \eta}}{\sigma_{\log \eta} \sqrt{t} \sqrt{2}} \right]$$



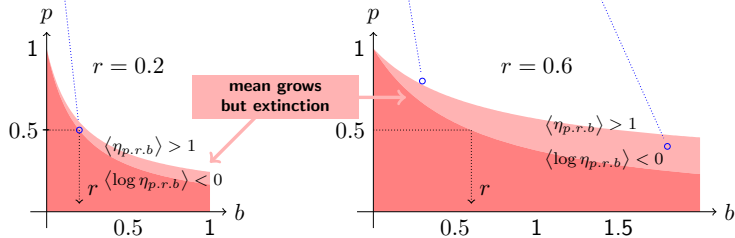
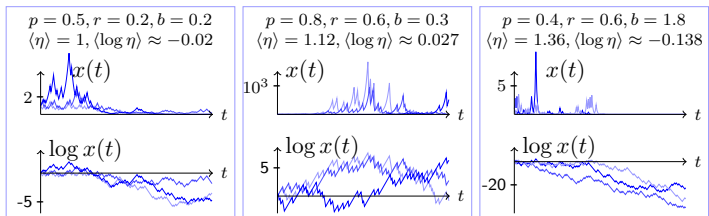
with $\mu_{\log \eta} = \langle \log \eta \rangle$, $\sigma_{\log \eta}^2 = \langle (\log \eta)^2 \rangle - \langle \log \eta \rangle^2$

- ▶ For $\mu_{\log \eta} < 0$: **Extinction!** (every quantile $\rightarrow 0$ with $t \rightarrow \infty$)
- For $\eta_{p,r,b}$

$$\langle \eta_{p,r,b} \rangle = p(1+b) + (1-p)(1-r)$$

$$\langle \log \eta_{p,r,b} \rangle = p \log(1+b) + (1-p) \log(1-r)$$

Behavior of $x(t+1) = \eta_{p,r,b}x(t)$



Input-output knowledge sharing

- Ensemble of n firms, with knowledge $x(0) \in \mathbb{R}_{>0}^n$
- Nonnegative **input-output matrix** A , a_{ij} is the fraction of knowledge i receives from j
- Dynamics

$$x(t+1) = Ax(t) = A^t x(0)$$

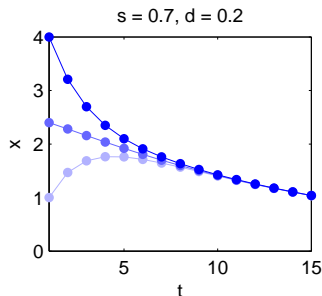
- As example s **keep self rate**, d **loss rate for shared**

$$A_{s,d} = \begin{bmatrix} s & \frac{(1-s)(1-d)}{n-1} & \cdots & \frac{(1-s)(1-d)}{n-1} \\ \frac{(1-s)(1-d)}{n-1} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \frac{(1-s)(1-d)}{n-1} \\ \frac{(1-s)(1-d)}{n-1} & \cdots & \frac{(1-s)(1-d)}{n-1} & s \end{bmatrix}$$

Lossy knowledge sharing

- For $n = 3$, $s = 0.7$, $d = 0.2$

$$A_{s,d} = \begin{bmatrix} 0.7 & 0.12 & 0.12 \\ 0.12 & 0.7 & 0.12 \\ 0.12 & 0.12 & 0.7 \end{bmatrix},$$



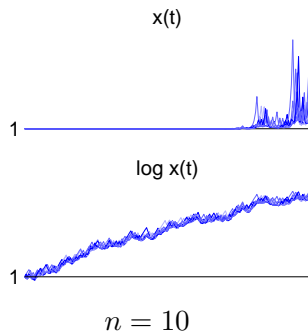
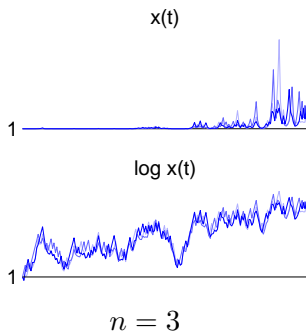
- Spectral radius $\rho(A_{s,d}) = 1 - d(1 - s) = 0.94$
- For $d > 0, s > 0$ Extinction!

Combination 1: Sharing of knowledge

For $s = 0.7, d = 0.2, p = 0.4, r = 0.6, b = 1.8$

- $\eta_{p,r,b}(t)$ now n -dim vector of iid random variables
- Knowledge shared by input-output matrix after production

$$x(t+1) = A_{s,d}(\eta_{p,r,b}(t)) \bullet x(t)$$

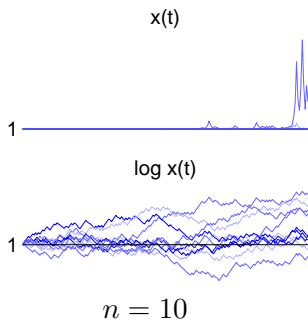
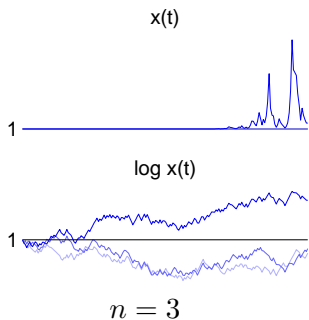


Combination 2: Sharing of potential

For $s = 0.7, d = 0.2, p = 0.4, r = 0.6, b = 1.8$

- $\eta_{p,r,b}(t)$ now n -dim vector of iid random variables
- Random growth rates are shared by input-output matrix

$$x(t+1) = (A_{s,d} \eta_{p,r,b}(t)) \bullet x(t)$$



Phase transitions

For $d = 0.2, p = 0.4, r = 0.6, b = 1.8$

- Intermediate **keep self rate** induces growth
- **More firms** can induce growth
- For 'potential': growth rate = $\exp \left\langle \log \left(s\eta + \sum_{i=1}^{n-1} \frac{(1-s)(1-s)}{n-1} \eta \right) \right\rangle$

