

# Heterogeneity in Signal Precision and Clustering of Defaults

A. K. Karlis<sup>1,3</sup>   G. Galanis<sup>2</sup>   S. Terovitis<sup>2</sup>   M. S. Turner<sup>1,3</sup>

<sup>1</sup>Department of Physics, University of Warwick, UK.

<sup>2</sup>Department of Economics, University of Warwick, UK.

<sup>3</sup>Complexity Center, University of Warwick, UK.

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## The leverage cycle in a nutshell:

- Leverage becomes too high in boom times, and too low in bad times.
- As a result, in boom times asset prices are too high, and in crisis times they are too low.

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- 1 The link between heterogeneity and the clustering of defaults.
- 2 Is a deterministic (non-linear) description of the default process feasible?

# Agent-based Framework

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# Agent-based Framework

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- Two kinds of traders:
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- **Credit:** The **HFs** can increase the size of their long position by borrowing from a bank using the asset as collateral.

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## Consequences of the fat-tail

- The scale-free character of the power-law distribution leads to clustering of defaults.
- The statistical properties of the default process, as viewed on the aggregate level, can be accurately described by an Intermittent (type III) process.



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- The price of the risky asset in the absence of the HFs is assumed to follow a mean-reverting AR(1) process.
- Thus, the demand (in cash value)  $\xi_t = D^{nt} p_t$  of the NTs follows

$$\log(\xi_t^{nt}) = \rho \log(\xi_{t-1}^{nt}) + (1 - \rho) \log(VN) + \sigma \chi_t, \quad (1)$$

where  $\chi_t = N(0, 1)$  and  $\rho \in (0, 1)$  (Poledna et al., 2014).

# Hedge Funds I

- HFs are represented by risk averse agents with CRRA.

# Funds

The maximization yields

$$D_t^j = \frac{m}{\alpha \sigma_j^2} W_t^j, \quad m = V - p_t. \quad (2)$$

- Demand is capped by  $\lambda^j = D_t^j p_t / W_t^j \leq \lambda_{\max}$ ,  
 $\lambda_{\max}$  the maximum allowed leverage set externally.

# Price

- The wealth of a HF evolves according to

$$W_{t+1}^j = W_t^j + (p_{t+1} - p_t)D_t^j - F_t^j \quad (3)$$

- $F_t^j$ , managerial fees following the 1/10 rule:

$$F_t^j = \gamma \left( W_t + 10 \max \{ W_t^j - W_{t-1}^j, 0 \} \right) \quad (4)$$

- The price of the risky asset is determined by the market clearance condition

$$D_t^{\text{nt}}(p_t) + \sum_{j=1}^n D_t^j(p_t) = N. \quad (5)$$

## Theorem

Consider an exponential density function  $P(\tau; \mu)$ , parametrized by  $\mu \in \mathbb{R}_+$ . Assume that  $\mu$  is itself a random variable with a density function  $W(\mu)$ . If  $W(\mu)$  can be expanded in a power-series, i.e.  $W(\mu) = \sum_{k=0}^{\infty} b_k \mu^k$ , for  $\mu \rightarrow 0^+$ , then the compound probability function defined as

$$\tilde{P}(\tau) \equiv \int_0^{\infty} W(\mu) P(\tau; \mu) d\mu$$

for  $\tau \gg 1$ , to the leading order of  $\mathcal{O}(1/\tau)$ , decays as  $\tilde{P}(\tau) \propto \tau^{-(n+2)}$ , where  $n$  is the order of the expansion around  $\mu = 0$ .

# Proof

## Proof.

The compound density is  $\mathcal{L}[\phi(\mu)]$ ,  $\phi(\mu) \equiv \mu W(\mu)$ , where  $\mathcal{L}[\cdot]$  denotes the Laplace transform with respect to  $\mu$ .

**Watson's Lemma:** If  $f(\mu)$  can be written as

$$f(\mu) = \mu^a \sum_{k=0}^m b_k \mu^k + R_{m+1}(\mu), \text{ with } a > -1, \text{ then}$$

$$\mathcal{L}[f(\mu)](\tau) \sim \sum_{k=0}^m b_k \frac{\Gamma(a+k+1)}{\tau^{a+k+1}} + \mathcal{O}\left(\frac{1}{\tau^{a+m+2}}\right). \quad (6)$$

Given that  $\phi(\mu) = \mu \sum_{k=0}^{\infty} b_k \mu^k$ ,  $\tilde{P}(\tau) \propto \tau^{-(n+2)} + \mathcal{O}\left(\frac{1}{\tau^{n+3}}\right)$ .



# Autocorrelation

## Theorem

Let  $T_n \in \mathbb{R}_+$ ,  $n \geq 0$ , be a sequence of i.i.d. random variables. Assume that the probability density function  $\tilde{P}(T_n = \tau) \propto \tau^{-\alpha}$ , for  $\tau \rightarrow \infty$ .

Consider now the renewal process  $S_n = \sum_{i=0}^n T_i$ . Let  $Y(t) = 1_{[0,t]}(S_n)$ , where  $1_A : \mathbb{R} \rightarrow \{0, 1\}$  denotes the indicator function, satisfying

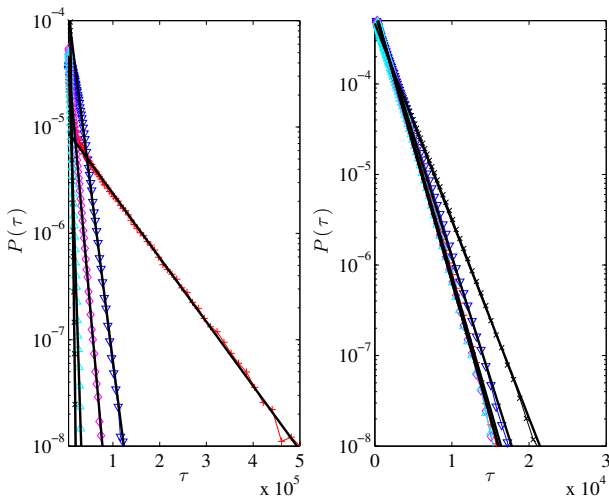
$$1_A = \begin{cases} 1 & : x \in A \\ 0 & : x \notin A \end{cases}$$

If  $2 < \alpha \leq 3$ , then the autocorrelation function of  $Y(t)$ , for  $t \rightarrow \infty$  decays as

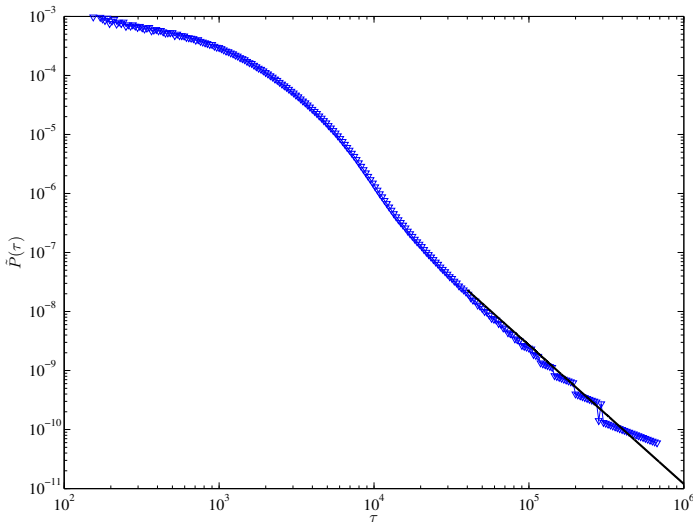
$$C(t') \propto t'^{2-\alpha} \tag{7}$$



# Failure Function — Microscopic Level



# After Aggregation



# Clustering of Defaults

## Asymmetric Information Leads to Clustering of Defaults

An important effect of the emergent heavy-tail statistics stemming from the heterogeneity of the market, is the absence of a characteristic time-scale for the occurrence of defaults (scale-free asymptotic behaviour).

# Clustering of Defaults

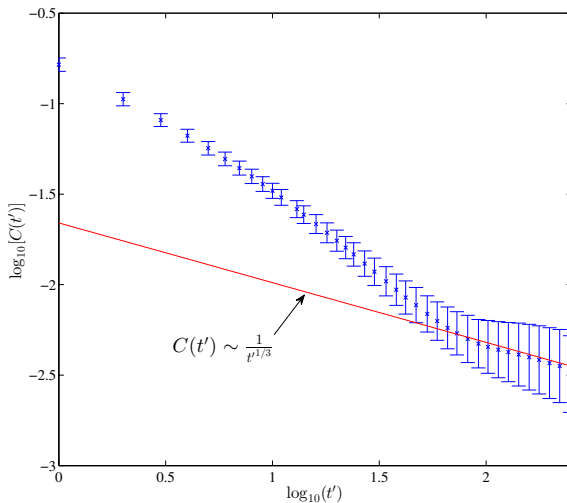
## Asymmetric Information Leads to Clustering of Defaults

An important effect of the emergent heavy-tail statistics stemming from the heterogeneity of the market, is the absence of a characteristic time-scale for the occurrence of defaults (scale-free asymptotic behaviour).

- Fitting the aggregate distribution we obtain  $\tilde{P}(\tau) \sim \tau^{-(7/3)}$ .
- According to Theorem 2, the autocorrelation function decays as,

$$C(t') \sim t'^{-1/3}. \quad (8)$$

# Autocorrelation Function



# Deterministic Description I

- All statistical properties of default events can be replicated by a very simple deterministic map.

$$x_{t+1} = x_t + ux_t^z \pmod{1}, \quad z > 1. \quad (9)$$

- Characteristic behaviour: The evolution of  $x_t$  is regular close to the vicinity of 0 (marginally unstable fixed point) and chaotic away from it  $\Rightarrow$  Random alternation between almost regular and chaotic dynamics.
  - Regular motion  $\rightarrow$  Laminar phase.
  - Chaotic motion  $\rightarrow$  Turbulent phase.

# Deterministic Description II

- The distribution of waiting times between transition from the laminar to the turbulent phase follows a power-law (Schuster and Just, 2006).

$$\rho(\tau) \propto \tau^{-\frac{z}{z-1}}, \quad (10)$$

- Also, the autocorrelation function of  $x_t$  decays algebraically

$$C(t') \propto t'^{\frac{z-2}{z-1}}, \quad 3/2 \leq z < 2. \quad (11)$$

Setting  $z = \frac{7}{4}$ , and mapping the:

- HFs Active  $\rightarrow$  Laminar phase.
- Default events  $\rightarrow$  Turbulent phase.

$$\rho(t) \sim \tau^{-7/3}, \quad C(t') = t'^{-1/3} \quad (12)$$

- We assume that the heterogeneity of the agents stems from the HFs' different quality of the mispricing signals they receive.
- We show that the failure function of the HFs is qualitatively different when observed on the micro and the aggregate level.
- We also show that the scale-free property of the emergent statistics on the aggregate level is directly connected with the clustering of defaults.



# Which is the Real Cause?

*... A crucial part of my story is heterogeneity between investors. . . But an important difference is that I do not invoke any asymmetric information. . . Of course, the asymmetric information revolution in economics was a tremendous advance, and asymmetric information plays a critical role in many lender-borrower relationships; sometimes, however, the profession becomes obsessed with it. . . (Geanakoplos, 2010)*

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