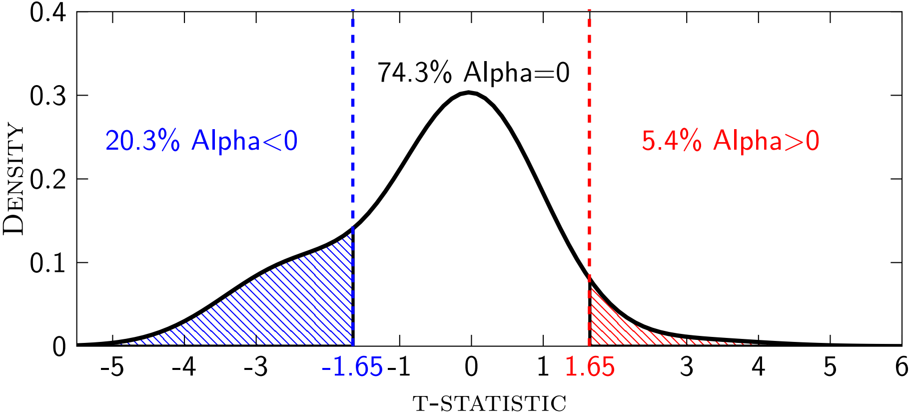
Social Interactions and the Performance of Mutual Funds

Julien Cujean

UNIVERSITY OF MARYLAND
ROBERT H. SMITH SCHOOL OF BUSINESS

LAEF 2016, Santa Barbara

A pervasive fact in the mutual fund industry

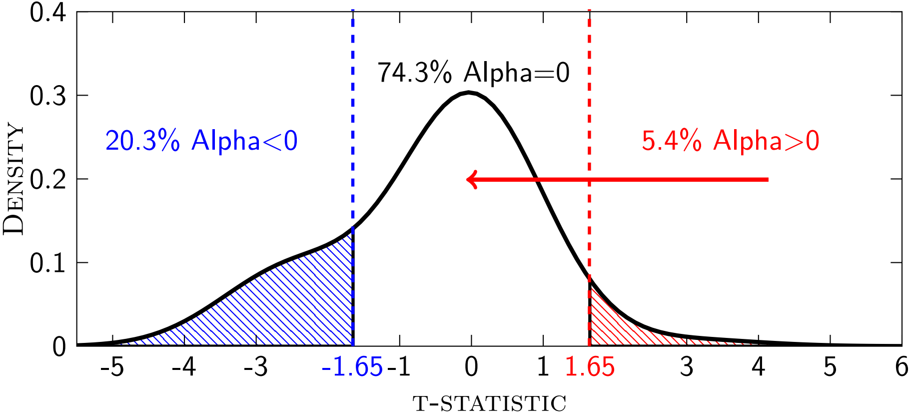


Cross-sectional distribution of alpha's t-stats

Skilled managers merely represent 2% of the population

Source: Barras, Scaillet & Wermers (JF, 2010)

A pervasive fact in the mutual fund industry

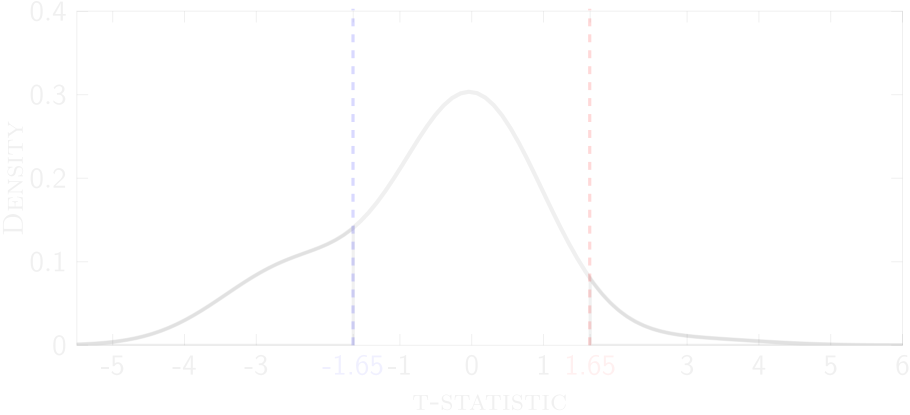


Cross-sectional distribution of alpha's t-stats

Managers do not maintain their performance

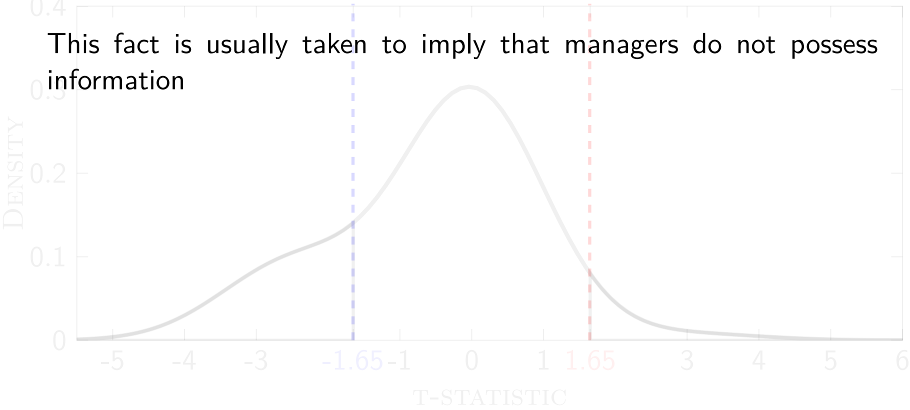
SOURCE: BARRAS, SCAILLET & WERMERS (JF, 2010)

Puzzling Evidence



Puzzling Evidence

This fact is usually taken to imply that managers do not possess information



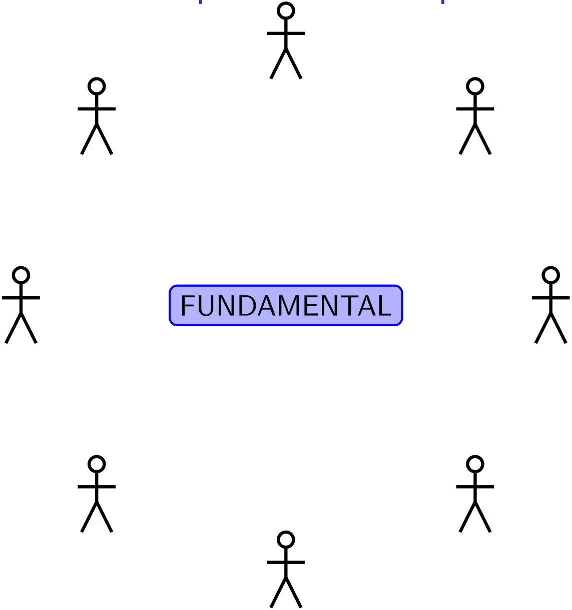
Puzzling Evidence

This fact is usually taken to imply that managers do not possess information

Puzzle: Strong evidence that managers do possess information e.g.:

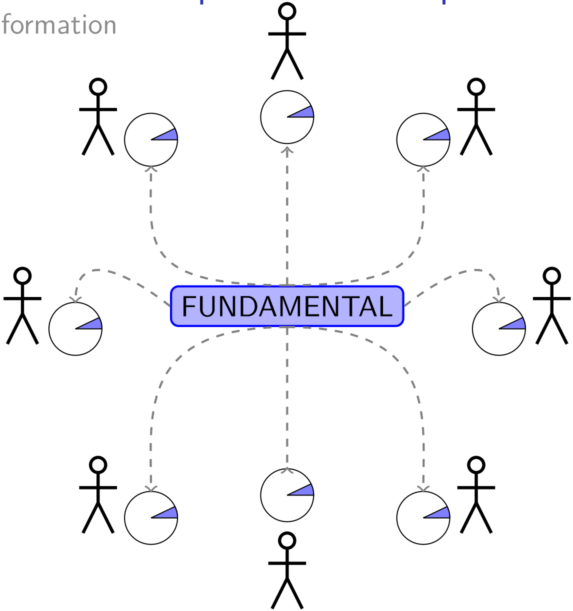
- Chevalier and Ellison (1999): SAT effect
- Coval and Moskowitz (2001): Local Informational Advantage
- Cohen et al. (2008): Educational Networks
- Christoffersen and Sarkissian (2009): Knowledge Spillovers

A Standard Rational-Expectations Setup



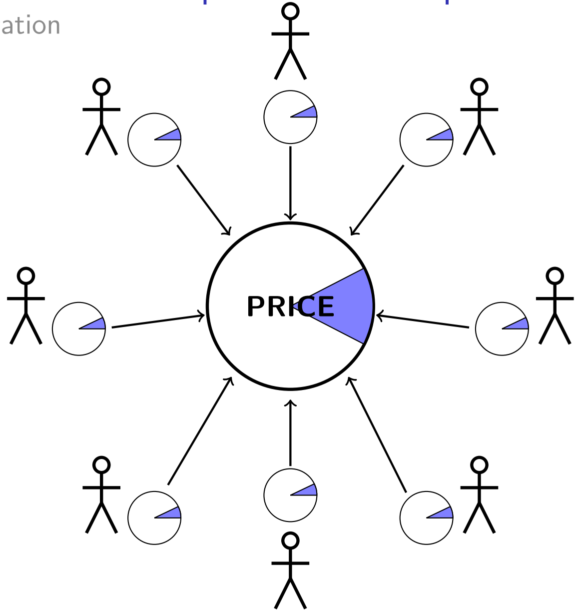
A Standard Rational-Expectations Setup

Dispersed Information



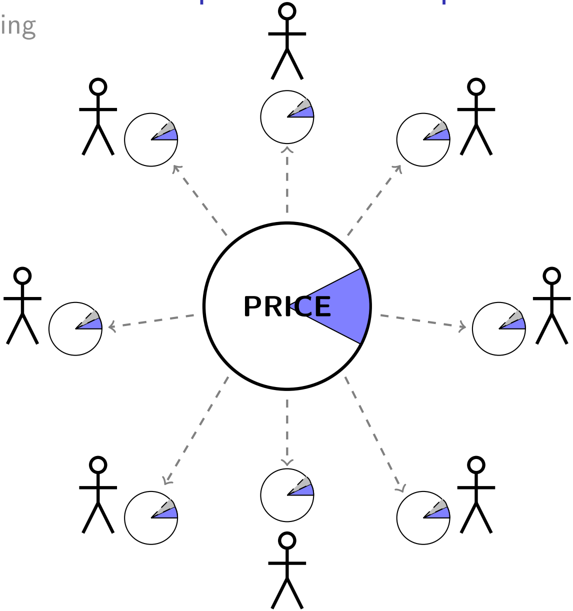
A Standard Rational-Expectations Setup

Aggregation



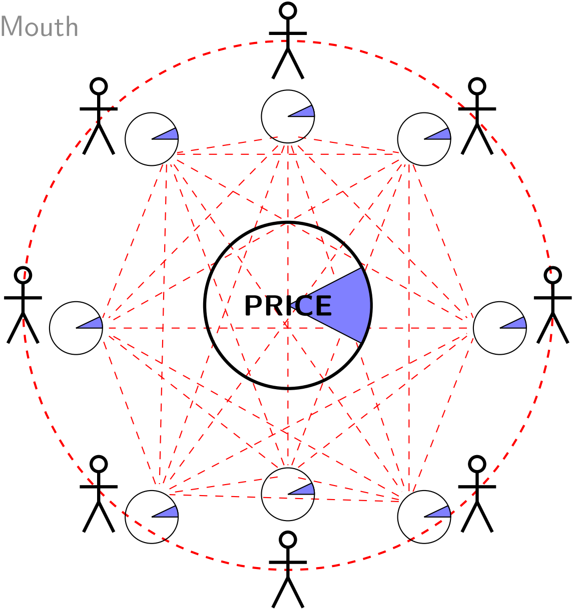
A Standard Rational-Expectations Setup

Learning



My Contribution

Word-of-Mouth



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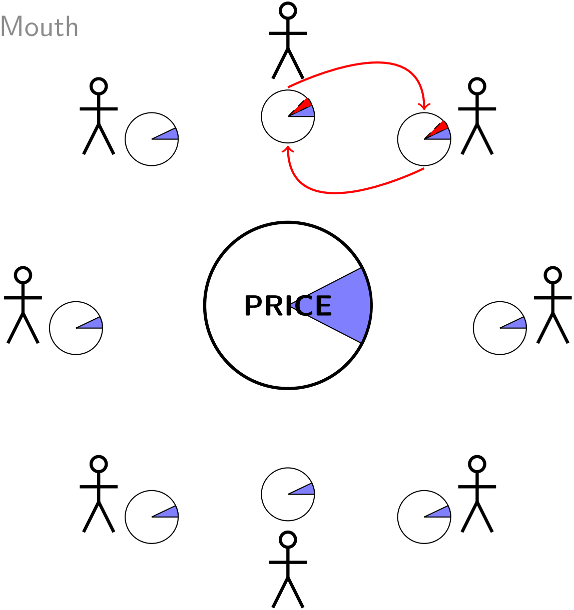

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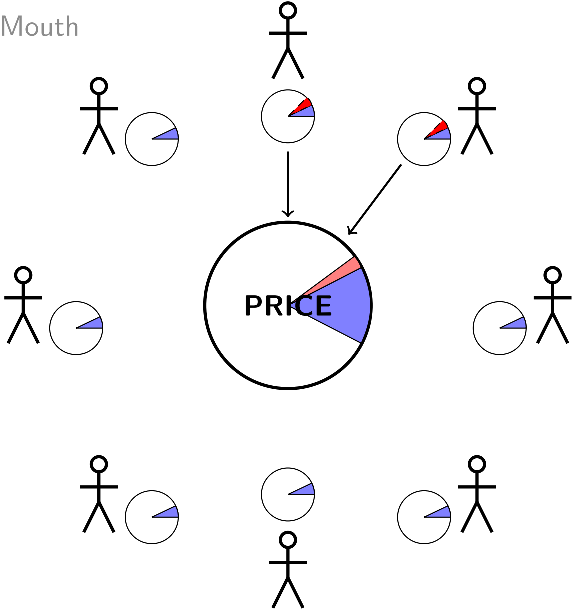

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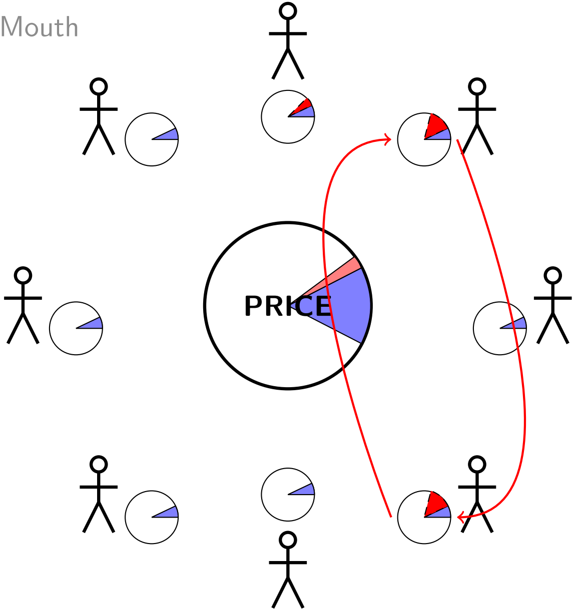

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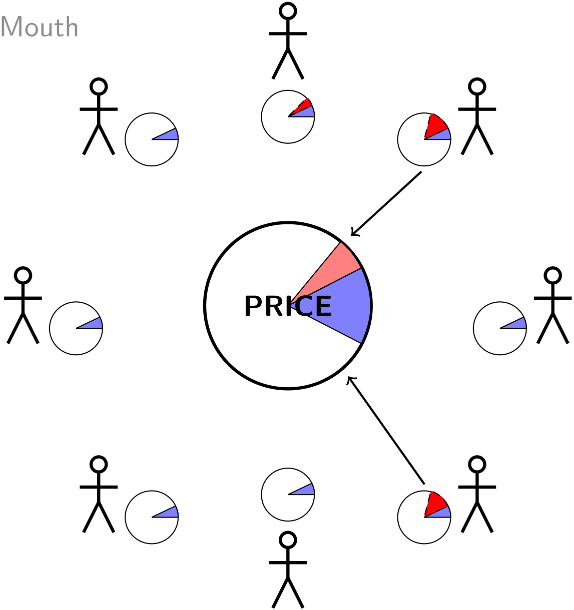

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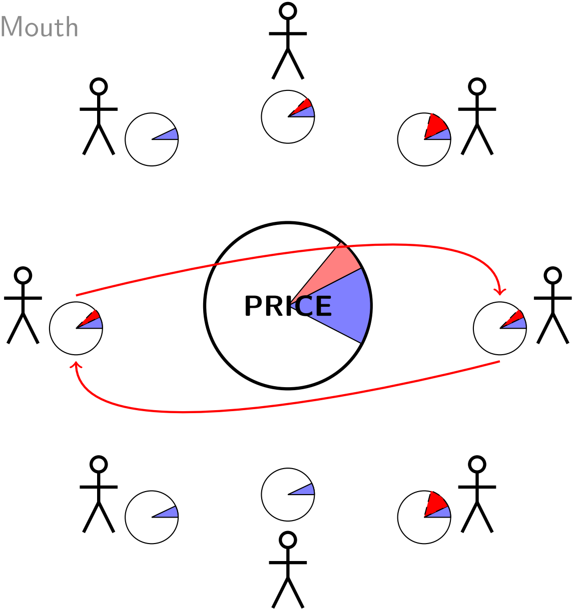

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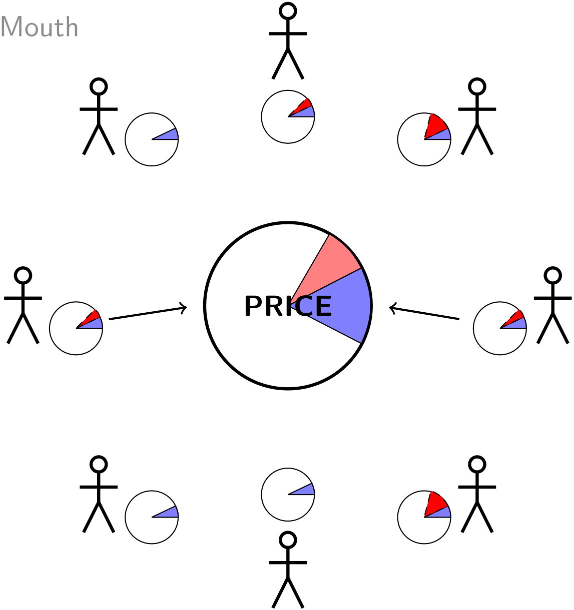

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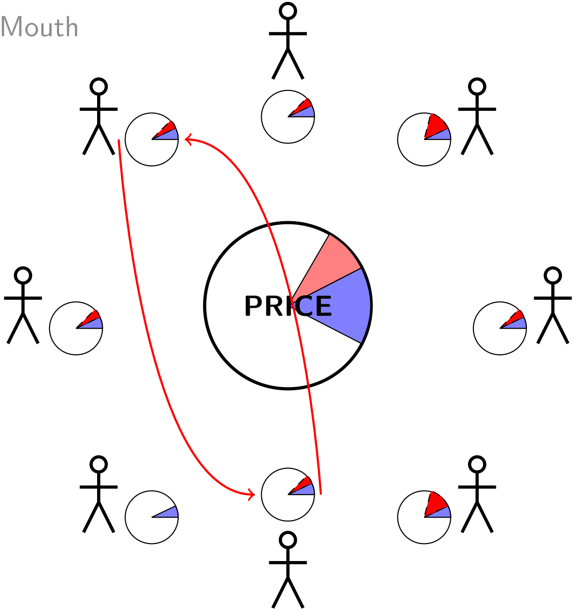

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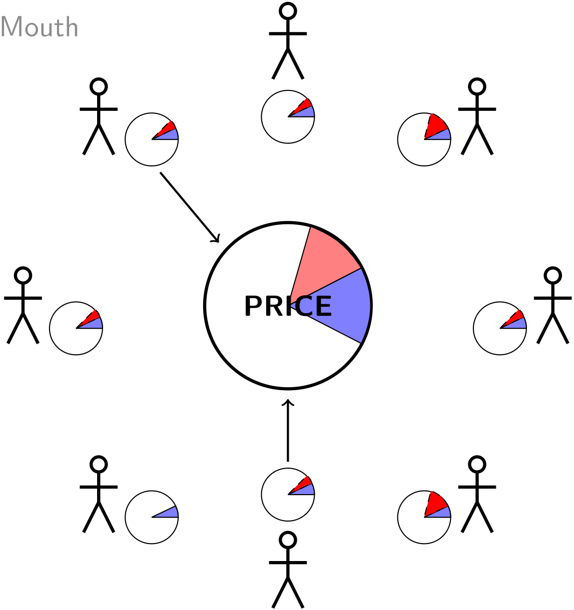

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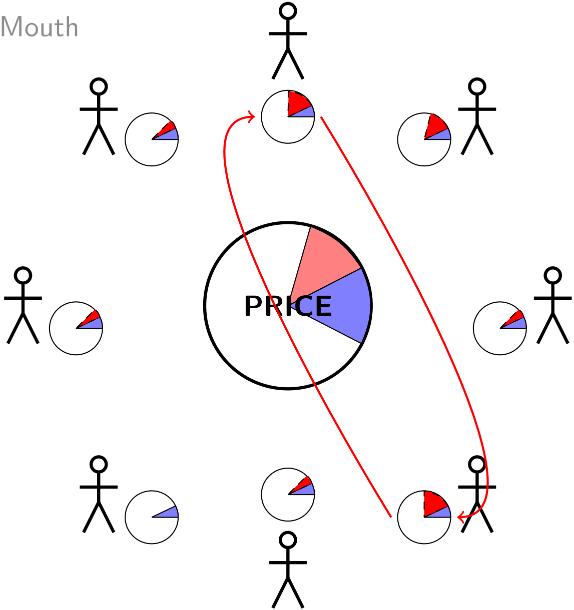

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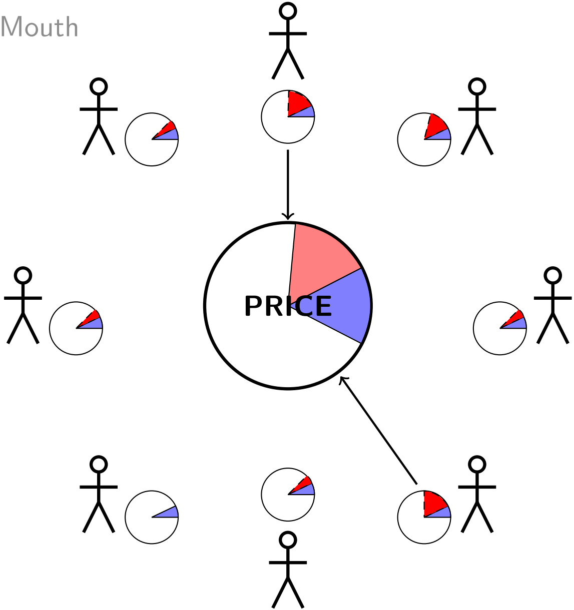

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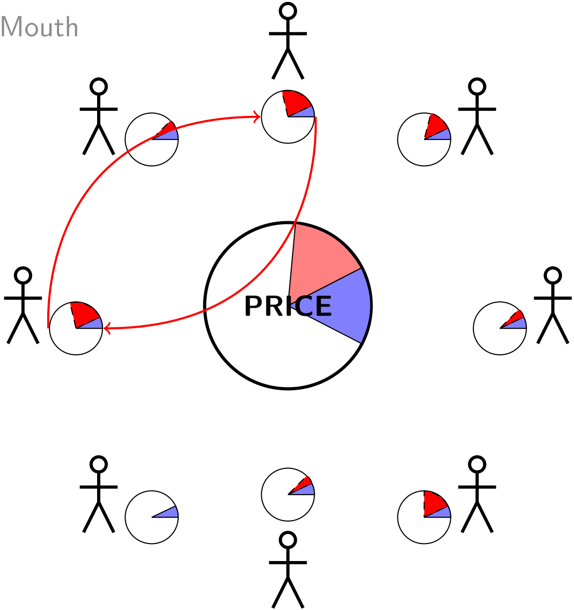

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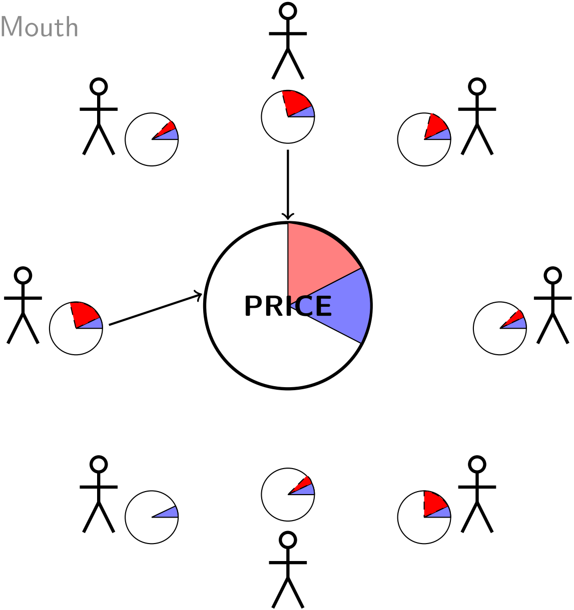

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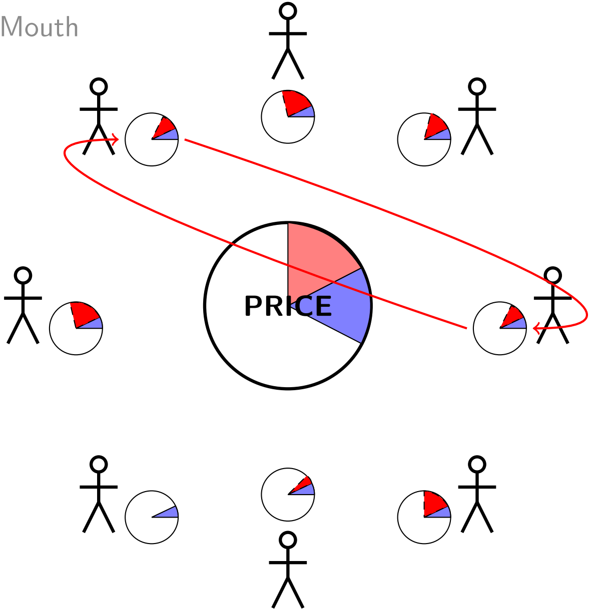

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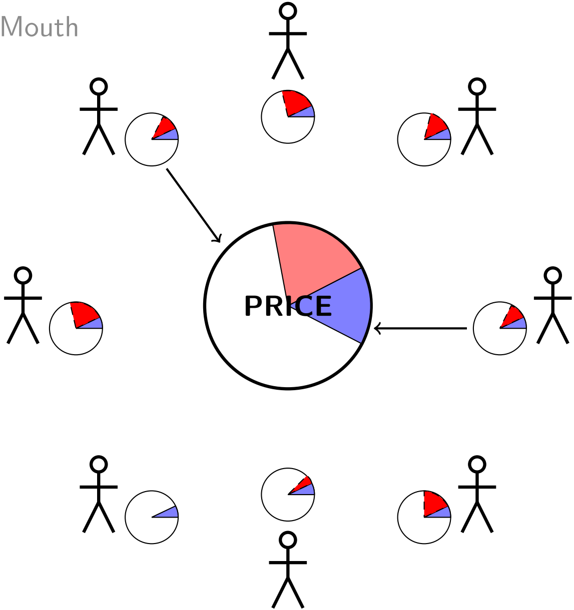

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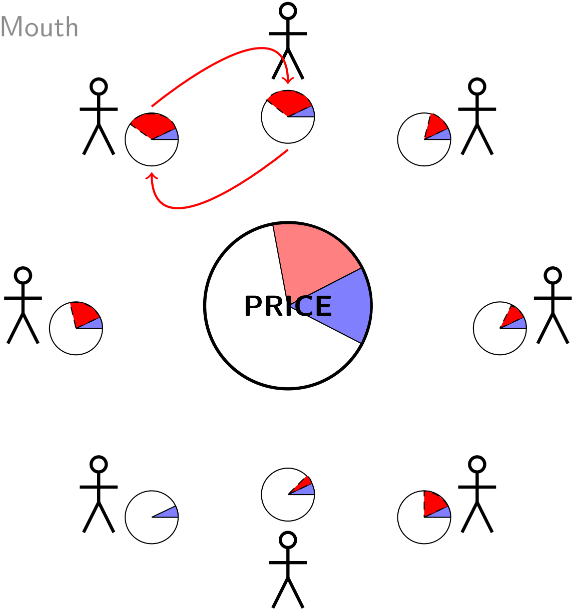

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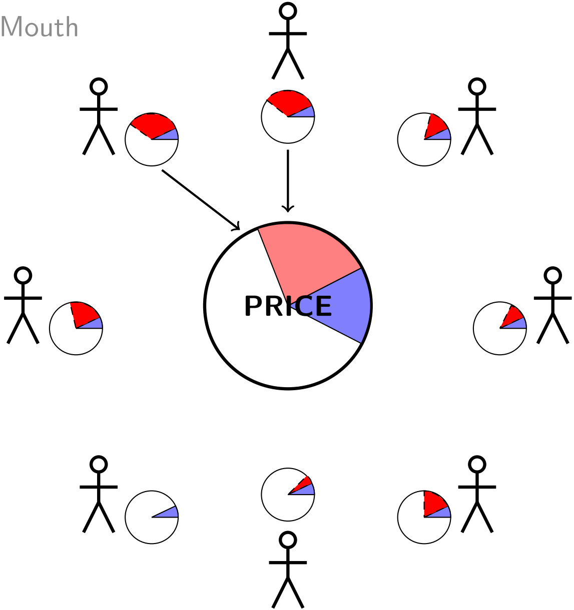
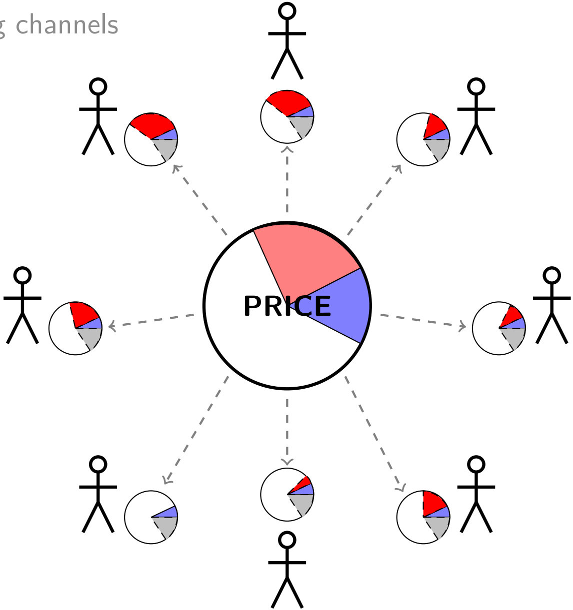


My Contribution

Two learning channels



Outline

I Model

II Solution Method

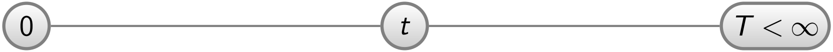
III Results

Outline

Setup

Setup

Continuous trading on $[0, T)$



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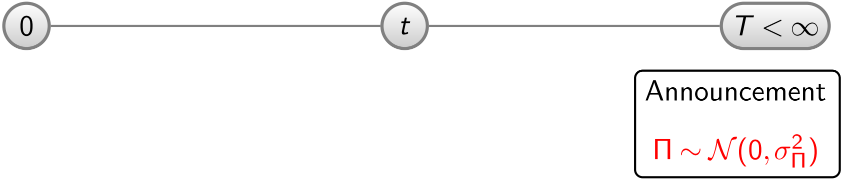

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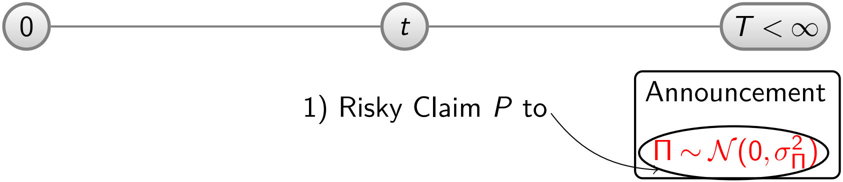

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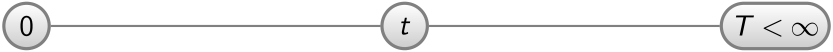

1) Risky Claim P to

Announcement

$\Pi \sim \mathcal{N}(0, \sigma_\Pi^2)$

2) Bond ($r = 0$)

Setup

Continuous trading on $[0, T)$

0 — t — $T < \infty$

Crowd of managers $i \in [0,1]$ with CARA=γ utility

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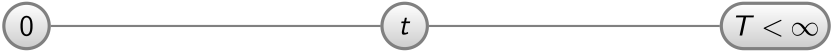

Crowd of managers $i \in [0,1]$ with CARA$=\gamma$ utility

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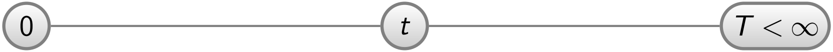
2) Bond $(r = 0)$

No fund flows: managers maximize $E[U[W_T^i]|\mathcal{F}_t^i]$, $\quad i \in [0,1]$

Setup

Continuous trading on $[0, T)$



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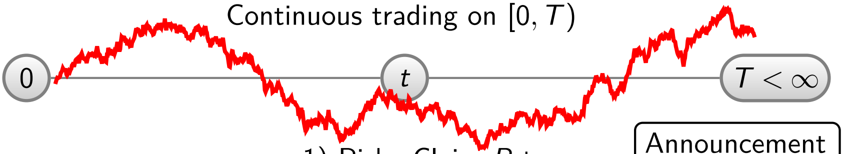
Noise Traders $\Longleftrightarrow$ noisy supply Θ_t

Setup



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Noise Traders $\iff$
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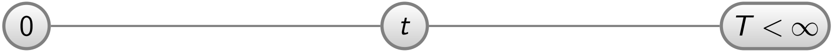
$$d\Theta_t = -a_\Theta \Theta_t dt + \sigma_\Theta dB_t^\Theta$$

Introducing Social Dynamics



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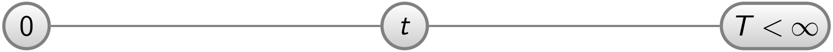

Each manager i starts with an idea $S_1^i = \Pi + \epsilon_1^i$

$$\{S_j^i\}_{j=1}^{1} = \{S_1^i\}$$

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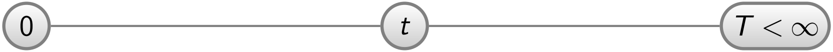

Each manager i starts with an idea $S_1^i = \Pi + \epsilon_1^i$

Managers meet at Poisson random times.
Ideas percolate with intensity η_t^i.

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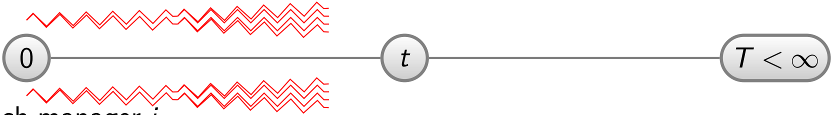

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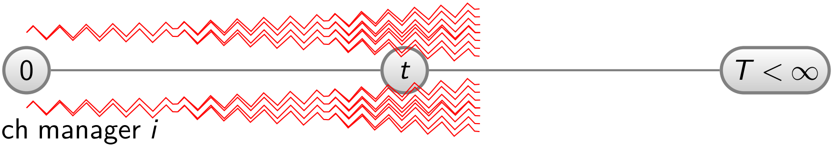
$$\{S_j^i\}_{j=1}^3 = \{S_1^i,\ S_2^i,\ S_3^i\}$$

Introducing Social Dynamics

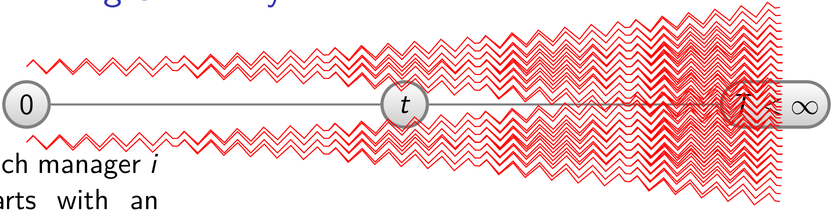


Each manager i starts with an idea $S_1^i = \Pi + \epsilon_1^i$

Managers meet at Poisson random times. Ideas percolate with intensity η_t^i.

$$\{S_j^i\}_{j=1}^6 = \{S_1^i,\ S_2^i,\ S_3^i,\ S_4^i,\ S_5^i,\ S_6^i\}$$

Introducing Social Dynamics



Each manager i starts with an idea $S_1^i = \Pi + \epsilon_1^i$

Managers meet at Poisson random times.
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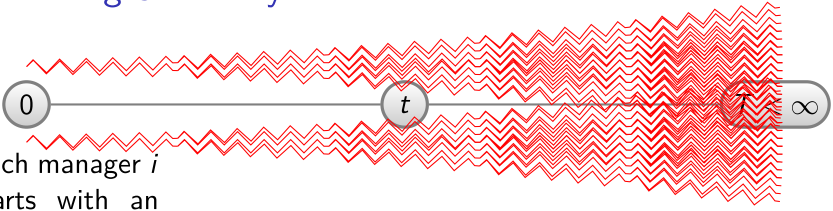
$$\{S_j^i\}_{j=1}^{n_t} = \{S_1^i,\ S_2^i, \ldots,\ S_{n_t}^i\}$$

Introducing Social Dynamics



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Managers meet at Poisson random times.
Ideas percolate with intensity η_t^i.

$$\{S_j^i\}_{j=1}^{n_t} \Longleftrightarrow Y_t^i \equiv \Pi + \frac{1}{n_t} \sum_{j=1}^{n_t} \epsilon_j^i$$

Introducing Social Dynamics

"*Relatively underdeveloped ideas can travel long distances over the network. More valuable ideas, by contrast, tend to remain localized among small groups of agents.*" Stein (2008)

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valuable ideas $n \geq N$

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# of ideas n: $[1, ..., N-1]$

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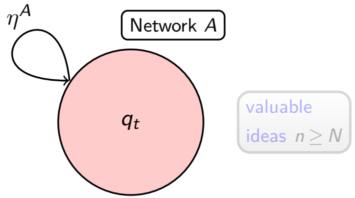

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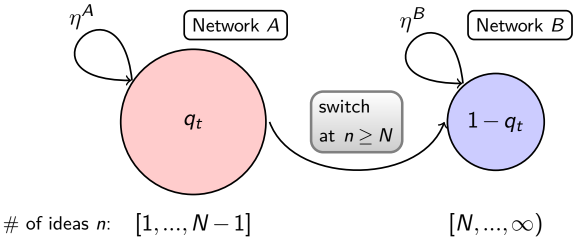

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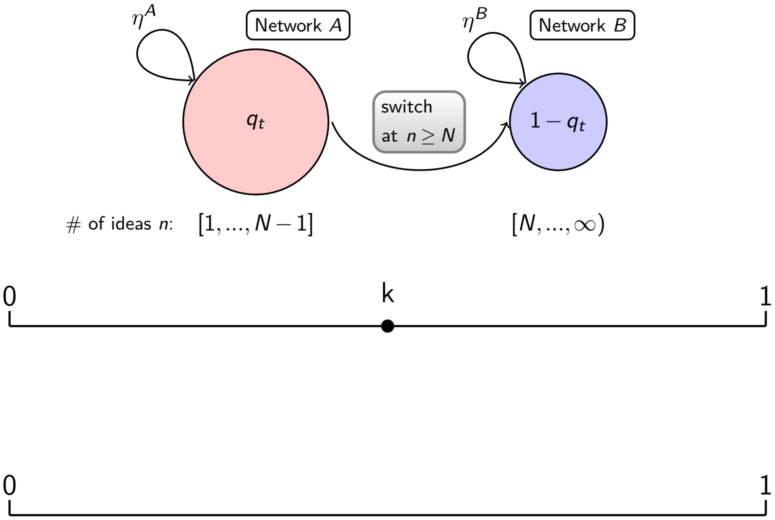

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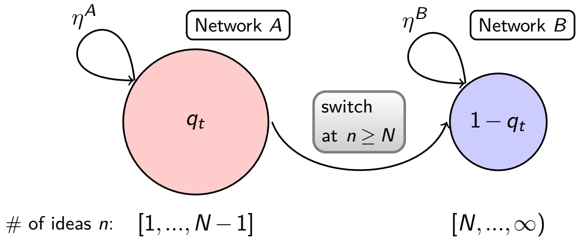

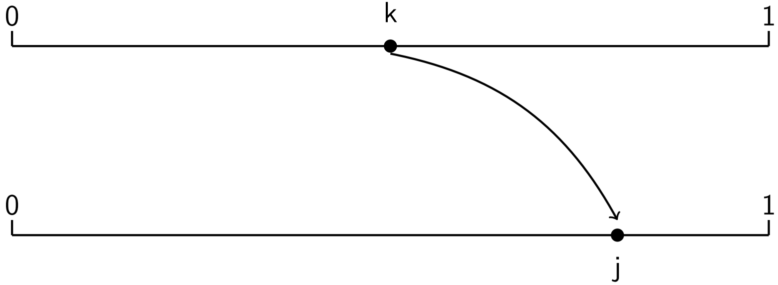

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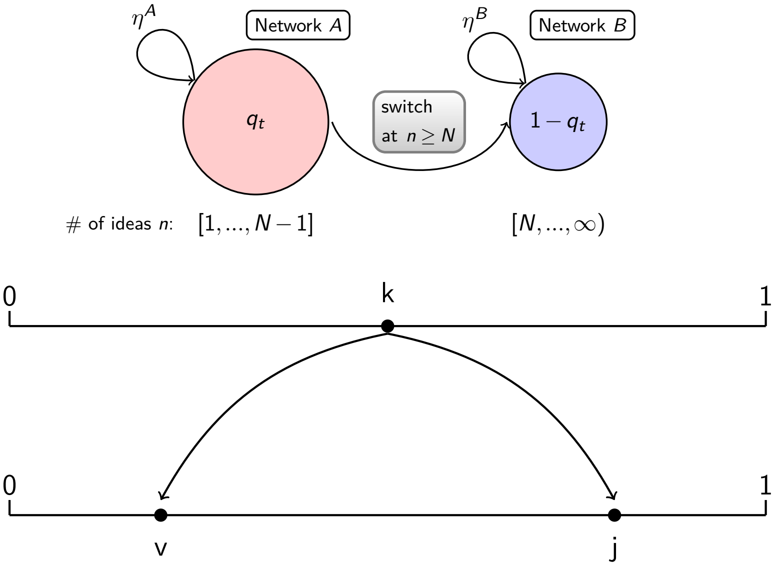

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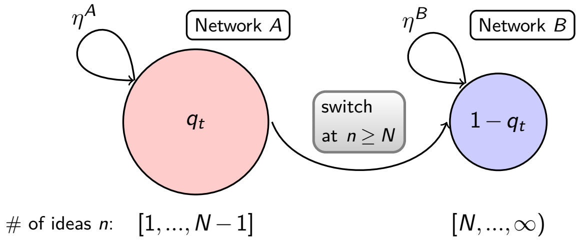

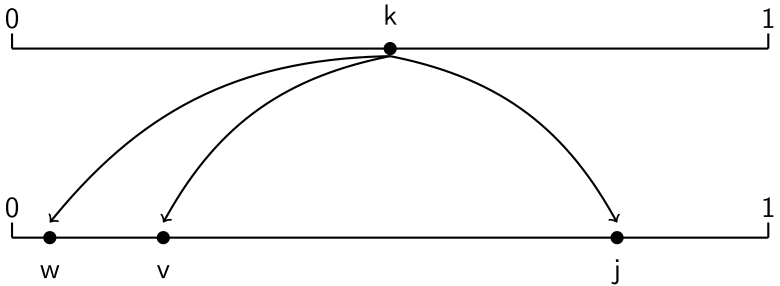

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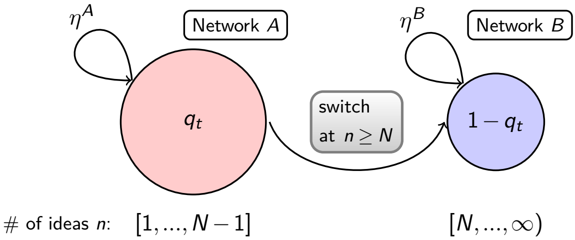

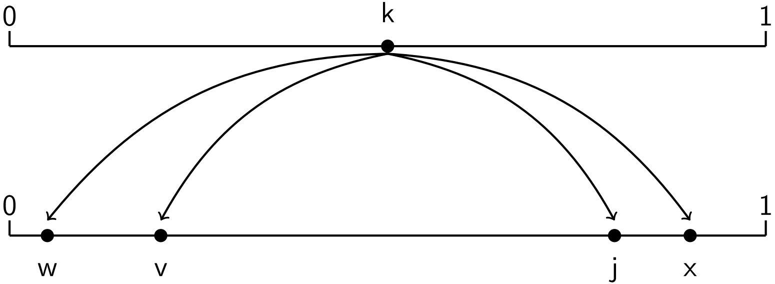

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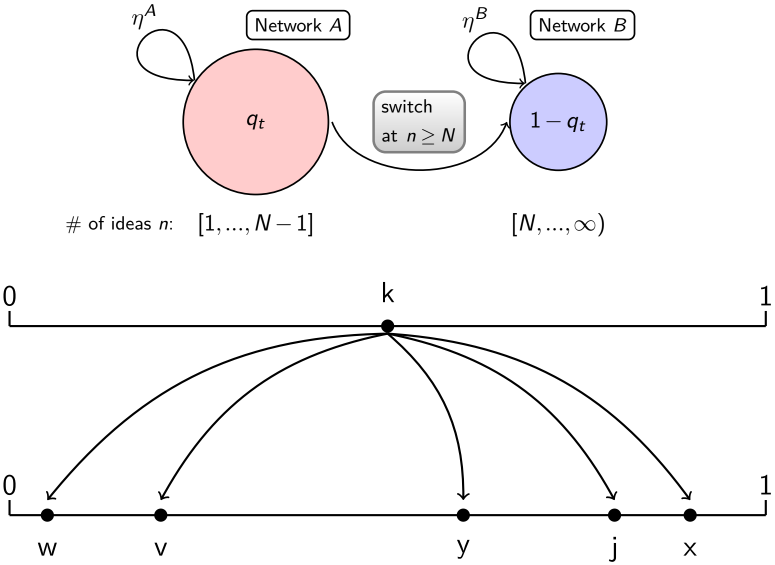

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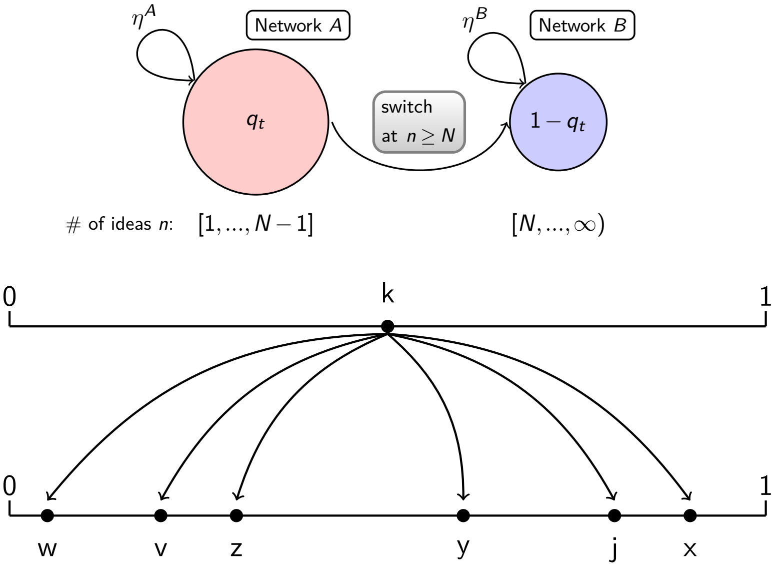

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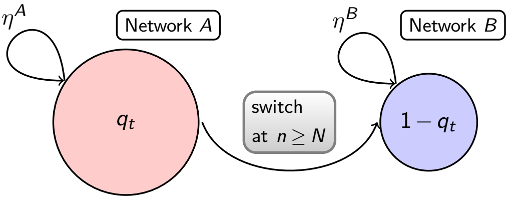

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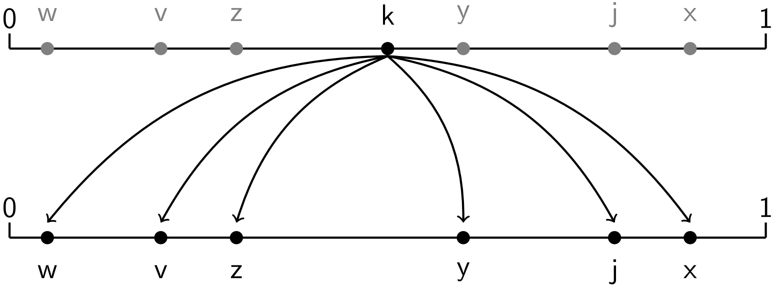

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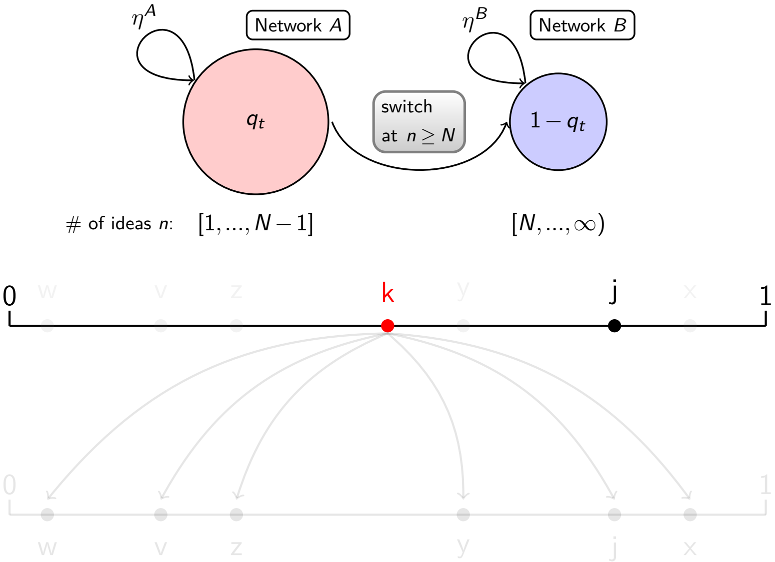

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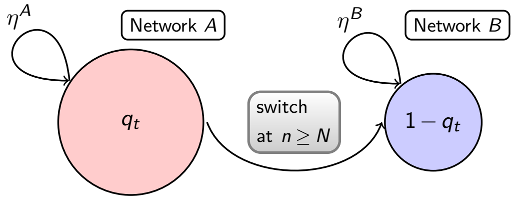

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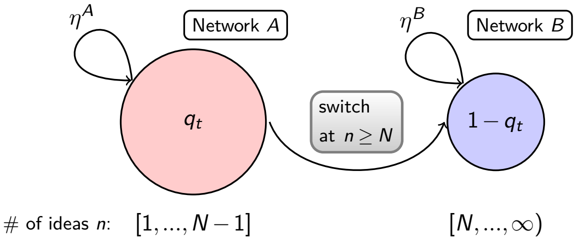
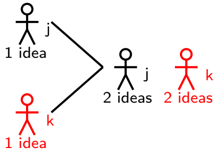
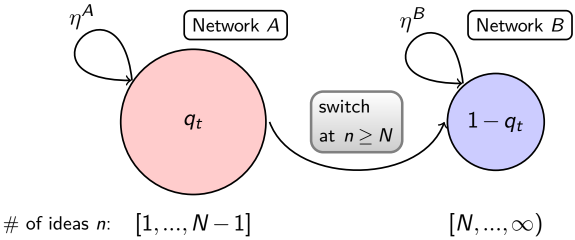
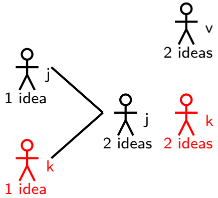




Introducing Social Dynamics





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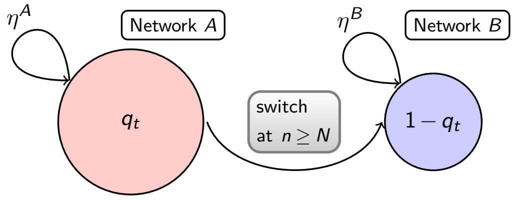
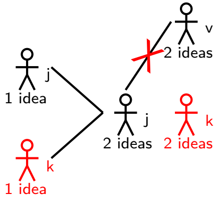


$\#$ of ideas n: $[1, ..., N-1]$ $[N, ..., \infty)$



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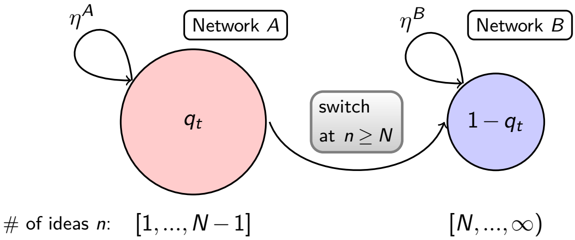

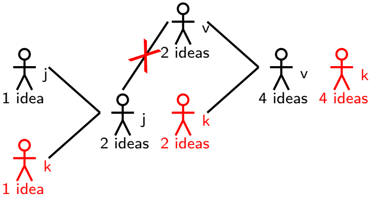

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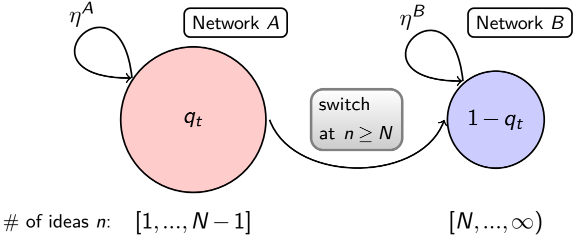

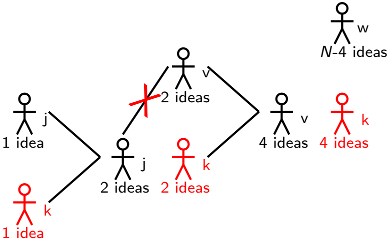

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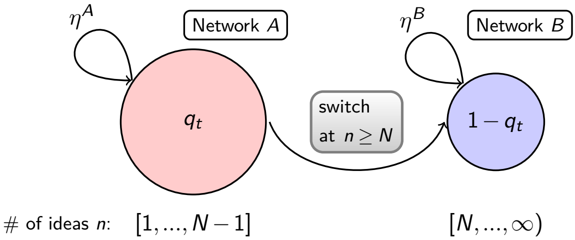

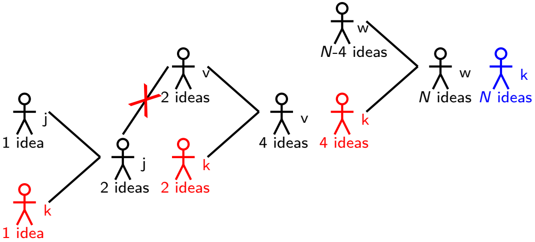

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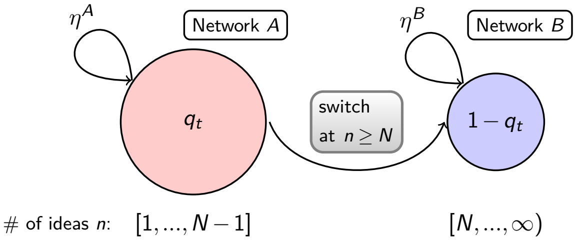

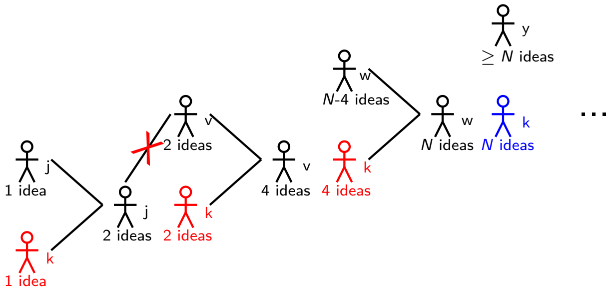

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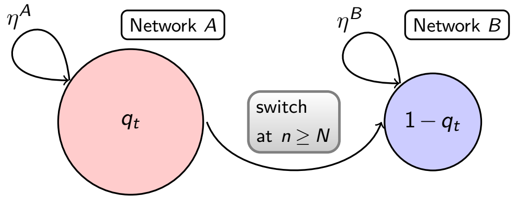


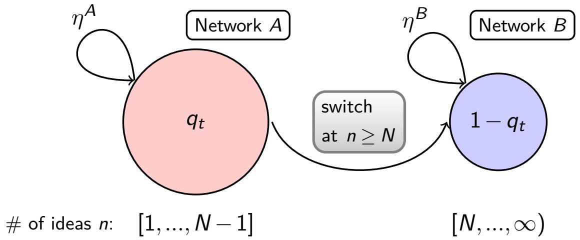
# of ideas n: $[1, ..., N-1]$ $[N, ..., \infty)$

Cross-Sectional Distribution of ideas

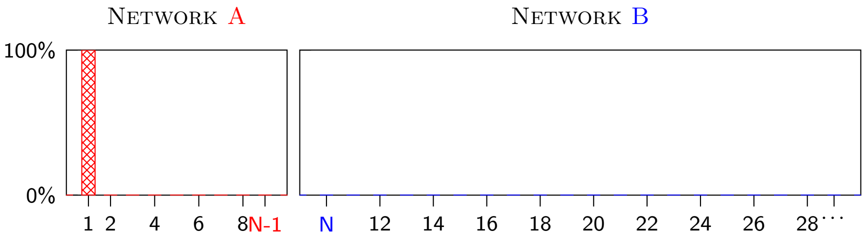
$$\frac{d}{dt}\mu_t(n) = \underbrace{\eta^A \mathbf{1}_{n<2N} \sum_{m=1 \vee (n-N+1)}^{(n-1)\wedge(N-1)} \mu_t(m)\mu_t(n-m) + \eta^B \mathbf{1}_{n\geq 2N} \sum_{m=N}^{n-N} \mu_t(m)\mu_t(n-m)}_{\text{Meetings}}$$

$$\underbrace{-\eta^A \mathbf{1}_{n\in A} q_t \mu_t(n) - \eta^B \mathbf{1}_{n\in B}(1-q_t)\mu_t(n)}_{\text{Replacements}}$$

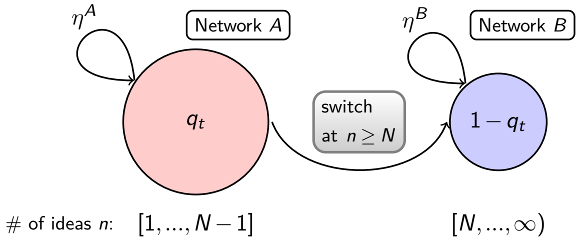
Introducing Social Dynamics



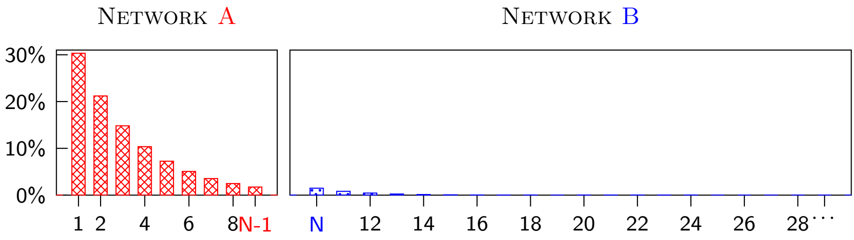
Cross-Sectional Distribution at time $t = 0$



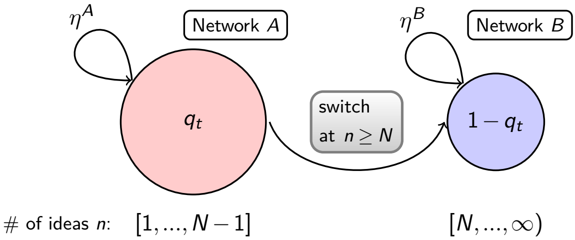
Introducing Social Dynamics



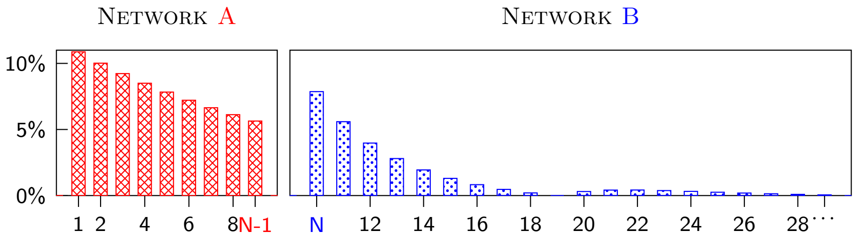
Cross-Sectional Distribution at time $t = 0.2$



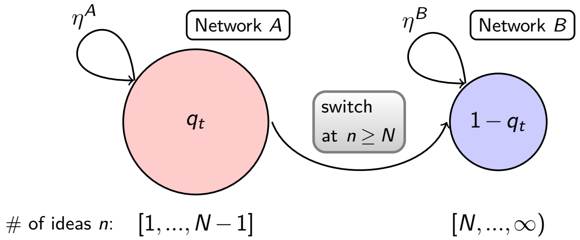
Introducing Social Dynamics



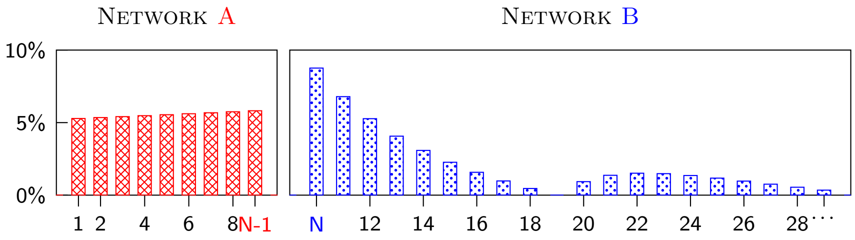
Cross-Sectional Distribution at time $t = 0.4$



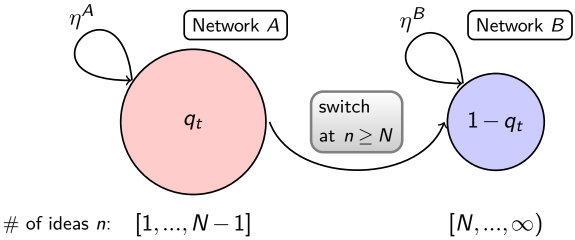
Introducing Social Dynamics



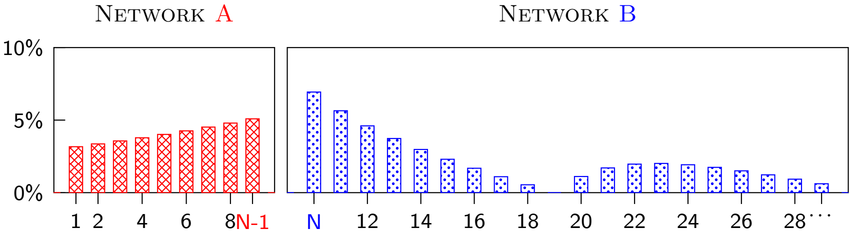
Cross-Sectional Distribution at time $t = 0.6$



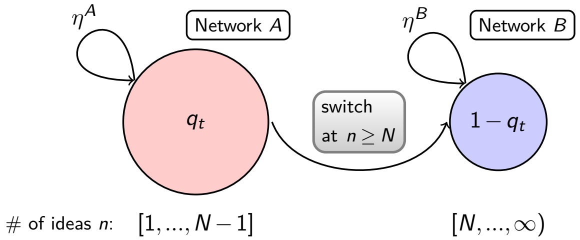
Introducing Social Dynamics



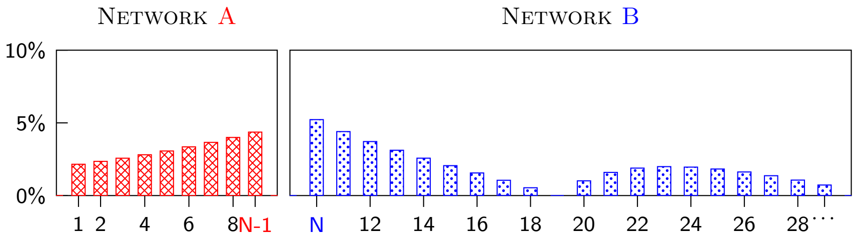
Cross-Sectional Distribution at time $t = 0.8$



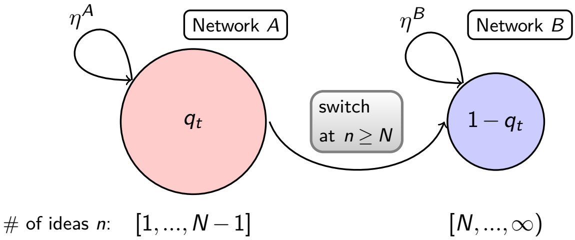
Introducing Social Dynamics



Cross-Sectional Distribution at time $t = 1$



Introducing Social Dynamics

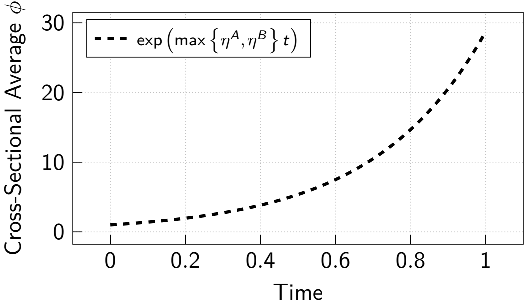


Cross-Sectional Average Number of ideas

$$\phi_t = b_t^{-\frac{\eta^B}{\eta^A}} e^{\eta^B t} \left(1 + \int_0^t e^{-\eta^B s} b_s^{\frac{\eta^B}{\eta^A}-1} \left((\eta^A + \eta^B) q_s - \eta^B\right) \frac{1 + a_s^{N-1}(a_s(N-1) - N)}{(1-a_s)^2} ds\right)$$

$$\leq \exp\left(\max\left\{\eta^A, \eta^B\right\} t\right)$$

Introducing Social Dynamics



Cross-Sectional Average Number of ideas

$$\phi_t = b_t^{-\frac{\eta^B}{\eta^A}} e^{\eta^B t} \left(1 + \int_0^t e^{-\eta^B s} b_s^{\frac{\eta^B}{\eta^A} - 1} \left((\eta^A + \eta^B) q_s - \eta^B\right) \frac{1 + a_s^{N-1}(a_s(N-1) - N)}{(1 - a_s)^2} \mathrm{d}s\right)$$
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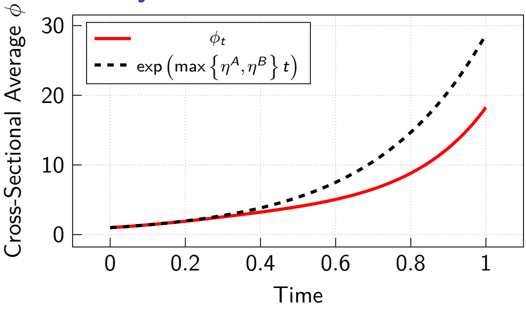
Introducing Social Dynamics



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$$\leq \exp\left(\max\left\{\eta^A, \eta^B\right\} t\right)$$

Outline

Steps (He and Wang (1995))

1. Price Conjecture

2. Learning Process

3. Individual Optimization

4. Market Clearing

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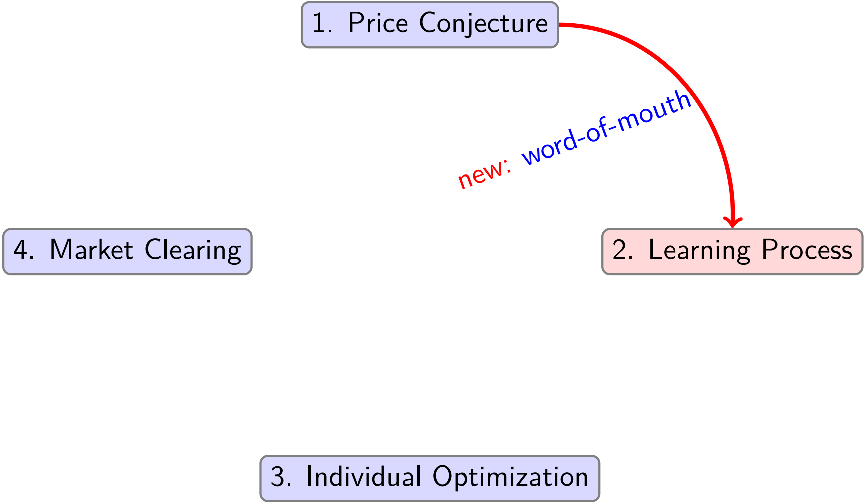

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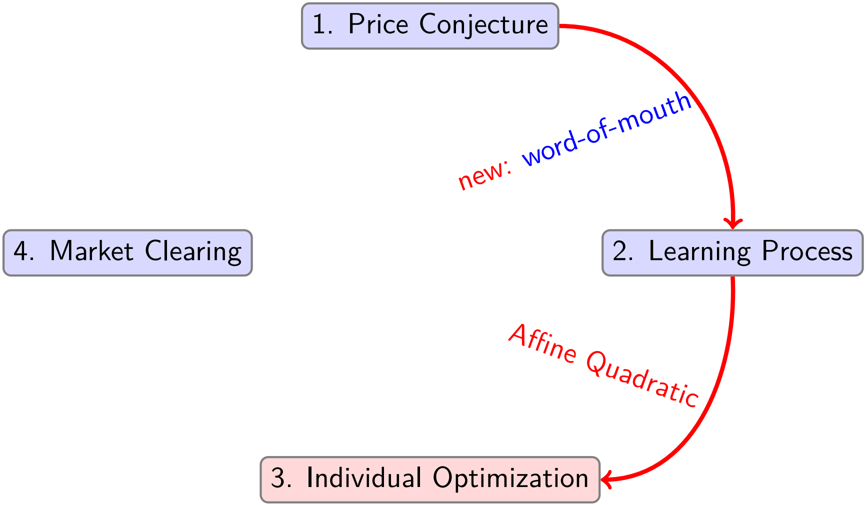

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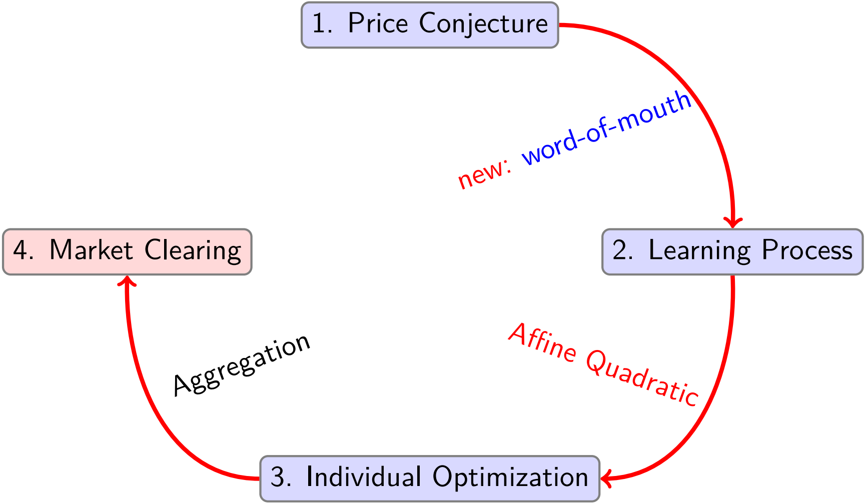

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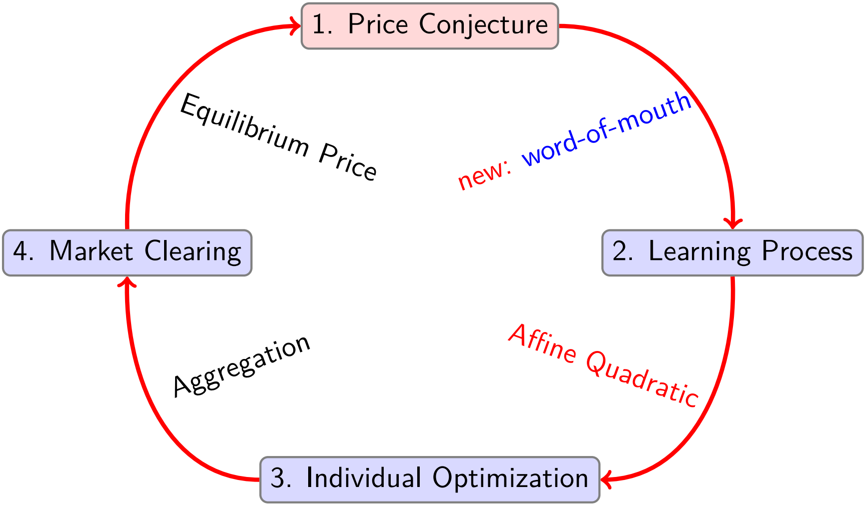

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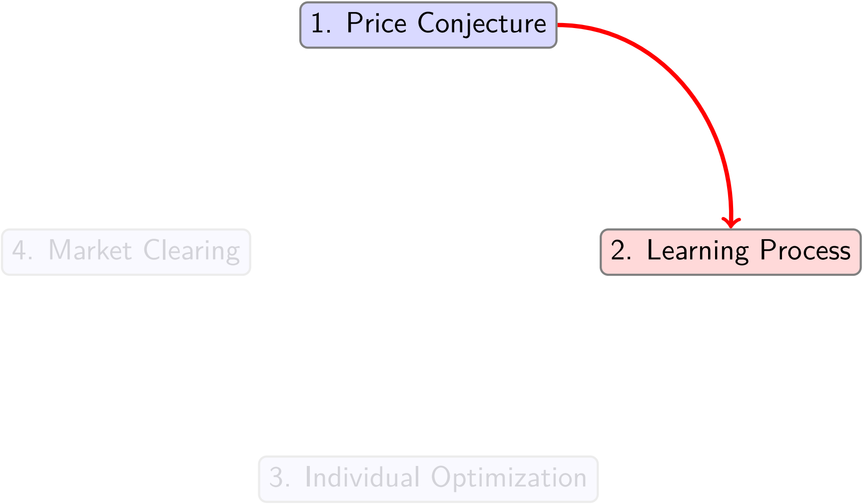

Word-of-Mouth Learning

A manager i's expectations evolve as

$$\mathrm{d}\widehat{\Pi}_t^i = o_{t-}^i k_t \mathrm{d}\widehat{B}_t^i + o_t^i \frac{\Delta n_t^i}{\sigma_S^2} \widehat{Y}_t^i \mathrm{d}N_t^i,$$

$$\mathrm{d}o_t^i = -k_t^2 (o_{t-}^i)^2 \mathrm{d}t - \frac{1}{\sigma_S^2} o_{t-}^i o_t^i \Delta n_t^i \mathrm{d}N_t^i$$

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MEETINGS

WATCHING THE TAPE

Word-of-Mouth Learning

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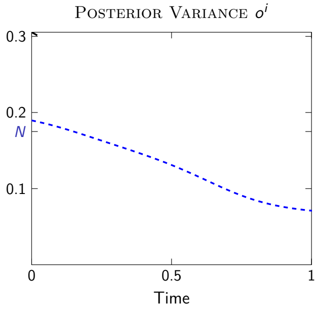

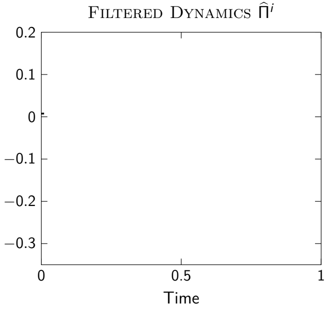

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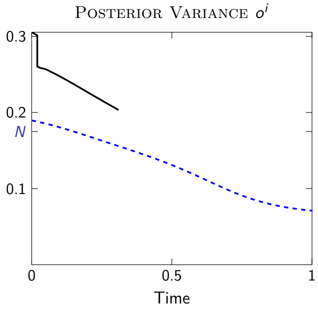

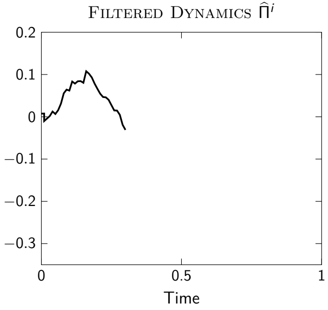

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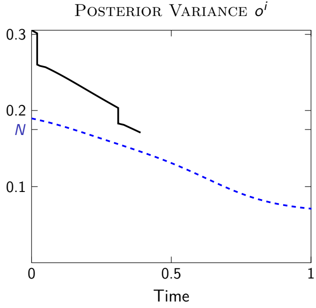

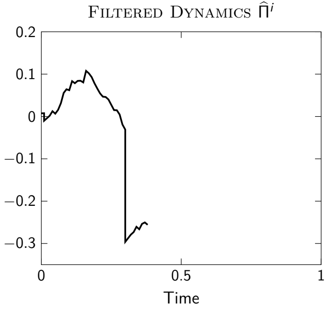

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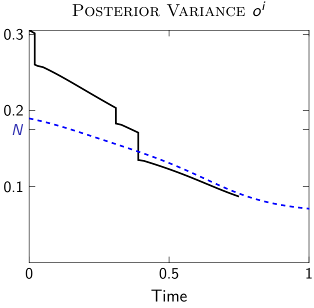

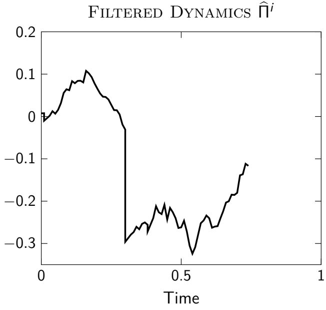

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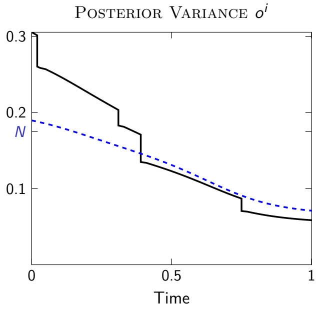
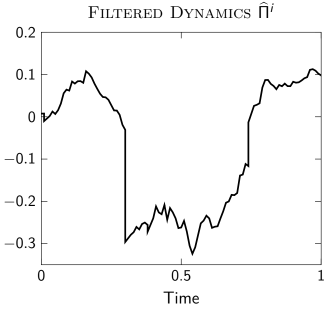
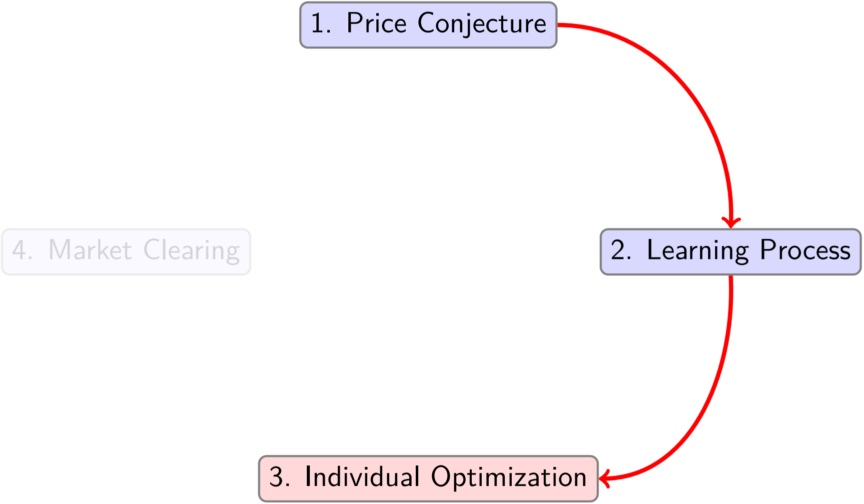




Steps (He and Wang (1995))



Social Interactions Increase Trading Aggressiveness

A manager i builds an optimal portfolio θ^i:

$$\theta_t^i = \frac{A_{Q,t} - B_{Q,t}\left(o_t(n^i)\right)^{-1} B_{\Psi,t}(n^i)^\top \Lambda_t}{\gamma B_{Q,t}^2} \begin{bmatrix} \widehat{\Pi}^i - \widehat{\Pi}^c \\ \widehat{\Theta}^i \end{bmatrix}$$

Social Interactions Increase Trading Aggressiveness

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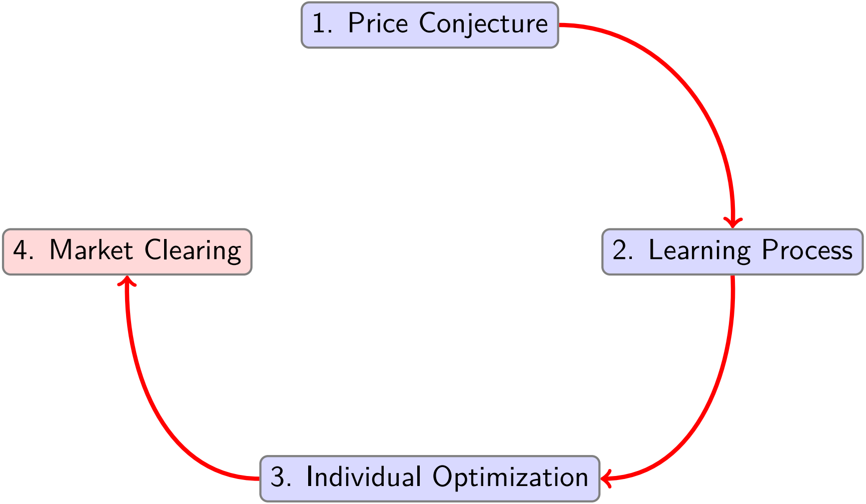
Informational Holdings

A manager i builds an optimal portfolio θ^i:

$$\theta^i_t = \underbrace{\Theta_t}_{\text{Market Making}} + \underbrace{\widehat{\theta}^i_t}_{\text{Informational Position}}$$

Steps (He and Wang (1995))



A Zero-Sum Game Among Managers

The market-clearing condition implies:

$$\int_{i \in I} \theta_t^i \mathrm{d}i = \underbrace{\Theta_t}_{\text{Market Making}} + \underbrace{\int_{i \in I} \widehat{\theta}_t^i \mathrm{d}i}_{\substack{\text{Informational Trading} \\ \equiv 0}} = \Theta_t.$$

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In equilibrium, the informational position satisfies

$$\widehat{\theta}_t^i = \underbrace{\frac{\sqrt{n^i}}{\gamma \sigma_S}}_{\substack{\text{Noise} \\ \text{(Luck)}}} \epsilon_t^i + \underbrace{\frac{\overbrace{n^i - \phi_t}^{\text{Skill}}}{\gamma \sigma_S^2 |k_t|} \times \text{Sharpe Ratio}}_{\text{Information}}$$

A Zero-Sum Game Among Managers

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In equilibrium, the informational position satisfies

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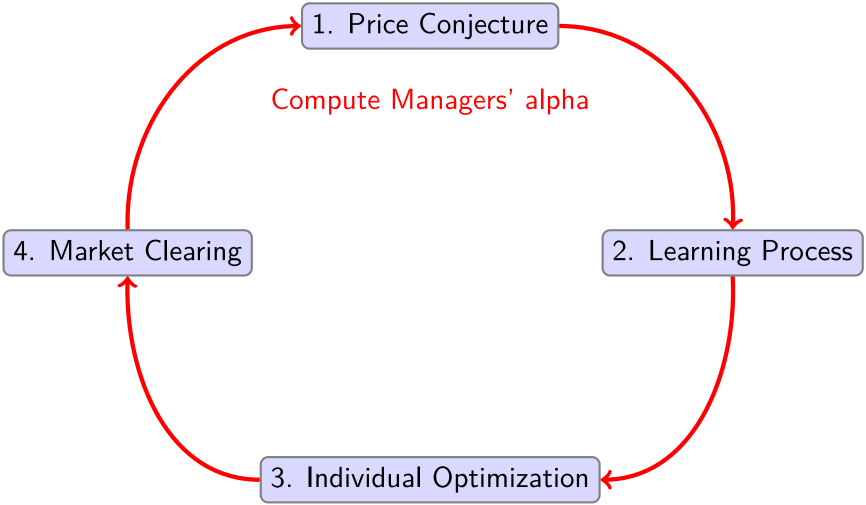
the average manager ($n^i \equiv \phi$) trades on noise only

Steps (He and Wang (1995))



Informational Alpha Estimation

The econometrician observes managers' returns $(\theta_t^i \mathrm{d}P_t)_{t\geq 0}$ and past prices $(P_t)_{t\geq 0}$ and thus managers' informational position $(\widehat{\theta}_t^i)_{t\geq 0}$:

$$\mathcal{F}_t = \sigma\left(\left(\Theta_s, \widehat{\theta}_s^i\right) : 0 \leq s \leq t, i \in [0,1]\right) \bigvee \sigma(\Pi), \ \ 0 \leq t < T.$$

Informational Alpha Estimation

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$$\mathcal{F}_t = \sigma\left(\left(\Theta_s, \widehat{\theta}_s^i\right) : 0 \leq s \leq t, i \in [0,1]\right) \bigvee \sigma(\Pi), \;\; 0 \leq t < T.$$

The econometrician runs the performance regression:

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Informational Alpha is a Noisy Measure of Skill

The unconditional estimate, $\widehat{\alpha}_t^i$, of manager i's alpha is

$$\widehat{\alpha}_t(n^i) = \underbrace{(n^i - \phi_t)}_{\text{Skill}} \frac{\sigma_S^4 k_t(k_t - \gamma\sigma_\Theta) o_t^c}{\gamma(\sigma_S^2 + o_t^c \phi_t)^3} \underbrace{\mathbb{E}[(\Delta_t^2 + \gamma o_t^c \Delta_t \Theta_t)^2]}_{\text{Market-Timing Gains (MTG)}}$$

Its unconditional $t-$statistic, $\widehat{t}_{\alpha,t}^i$, is given by

$$\widehat{t}_{\alpha,t}(n^i) = \sqrt{\frac{2}{\pi}} \mathbb{E}\left[\text{Sharpe Ratio}(\Delta_t^2 + \gamma o_t^c \Delta_t \Theta_t)\right] \frac{\text{sign}(n^i - \phi_t)}{\sqrt{\text{MTG} + \left(\underbrace{\frac{\sigma_S}{\sigma_S^2 + o_t^c \phi_t} \frac{n^i - \phi_t}{\sqrt{n^i}}}_{\text{Skill-to-Luck Ratio}}\right)^{-2}}}.$$

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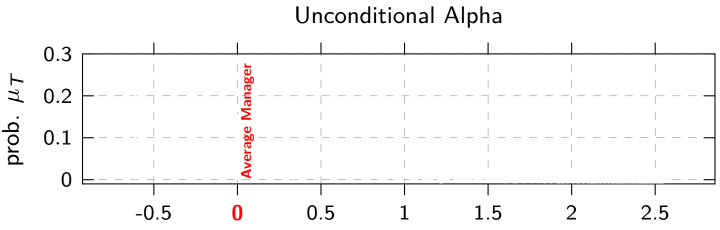
Outline

I Model

II Solution Method

III Results

Cross-Sectional Performance



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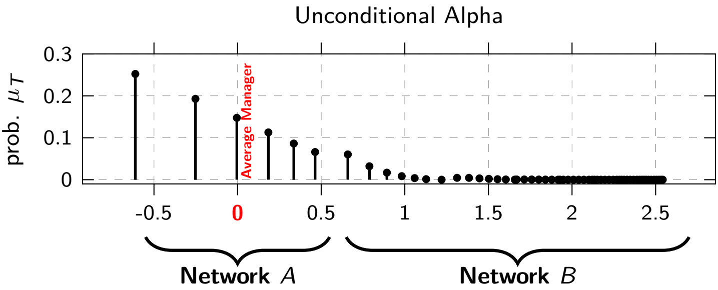

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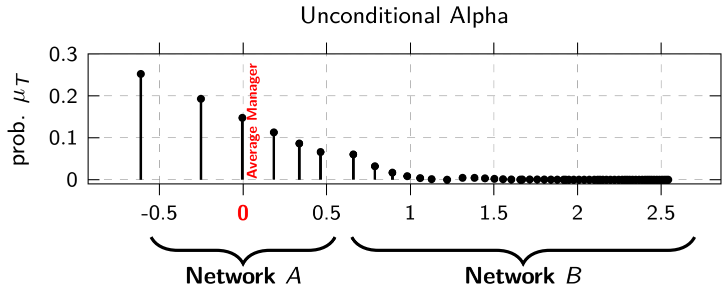
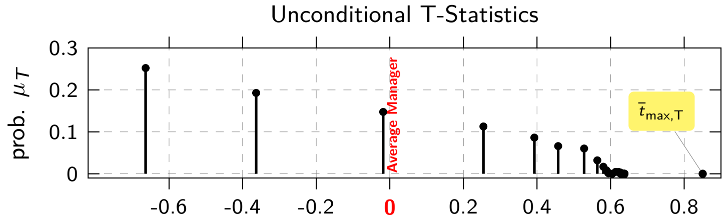
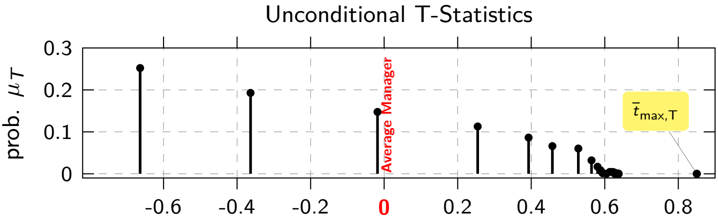




Cross-Sectional Performance

A manager's $t-$statistic depends on her skill-to-luck ratio:

$$t_{\alpha,t}(n^i) = (-1)^{\mathbf{1}_{n^i<\phi_t}} \sqrt{\frac{2}{\pi}} \frac{\sigma_S^2|k_t|}{\sigma_S^2+o_t^c\phi_t} \frac{\text{Timing Gains}}{\sqrt{\text{Timing Gains} + \underbrace{\frac{\sigma_S}{\sigma_S^2+\phi_t o_t^c} \frac{n^i-\phi_t}{\sqrt{n^i}}}_{\text{Skill-to-Luck Ratio}}}}$$



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1. In a standard REE with a Brownian flow of information (He and Wang (1995) in continuous time), the average rate of information arrival is $\phi_t = t$ and

$$t_{max,0}^{(1)} = \sqrt{\frac{2}{\pi}} \frac{\text{fundamental noise}}{\text{total noise}} \quad \text{and} \quad \bar{t}_{max,\infty}^{(1)} = \lim_{T \to \infty} \frac{1}{T} \int_0^T t_{max,s}^{(1)} ds = 0.$$

2. In this model with Network A only, the average rate of information arrival is $\phi_t = \exp(\eta^A t)$ and

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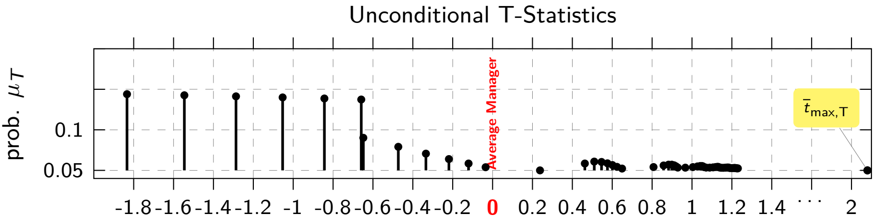

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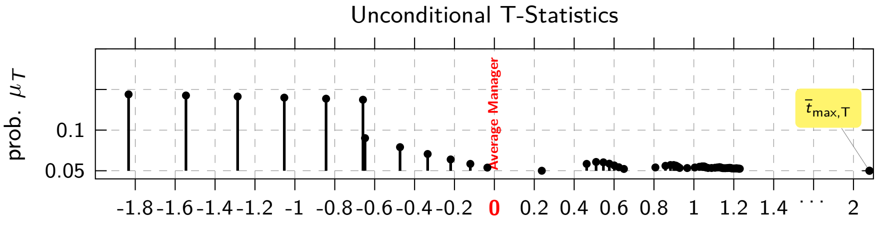
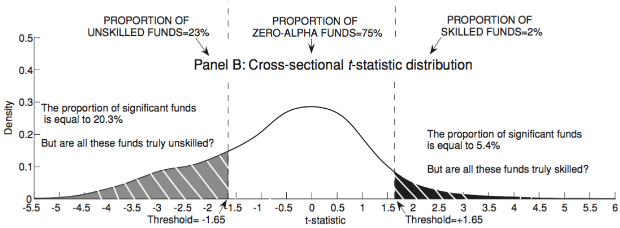
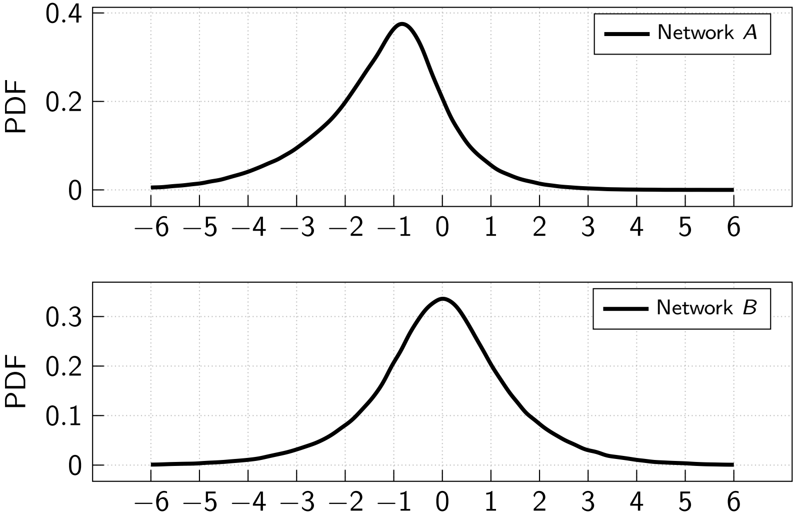




Source: Barras, Scaillet & Wermers (JF, 2010)

The Role of Luck



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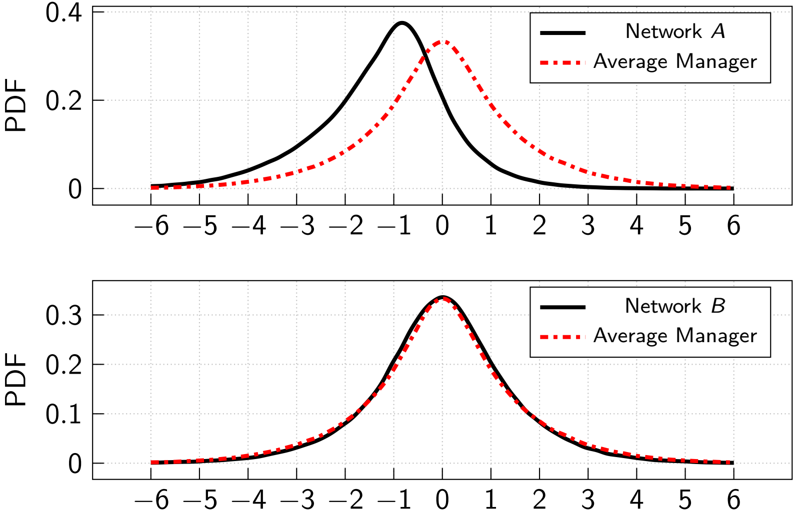

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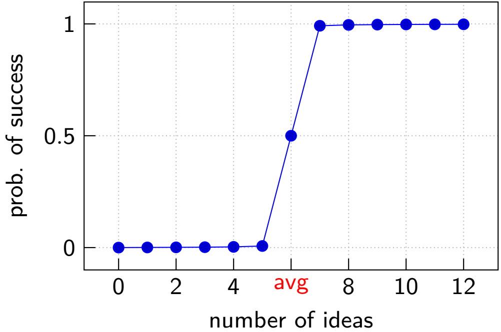

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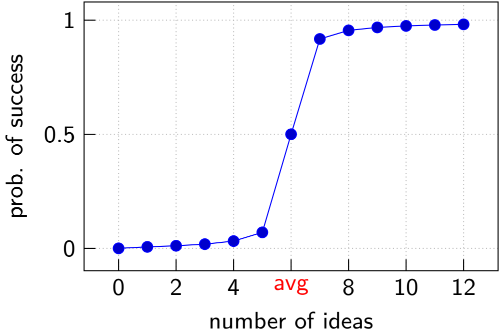

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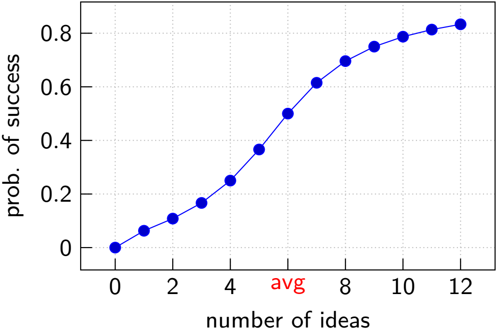

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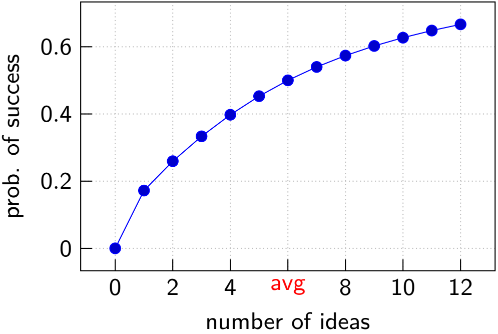

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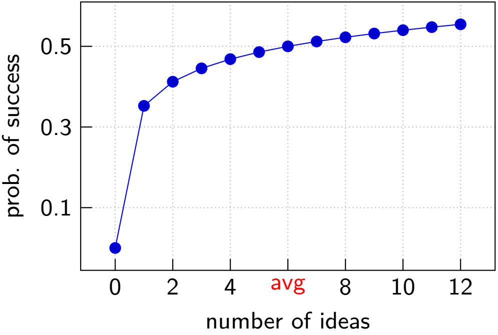

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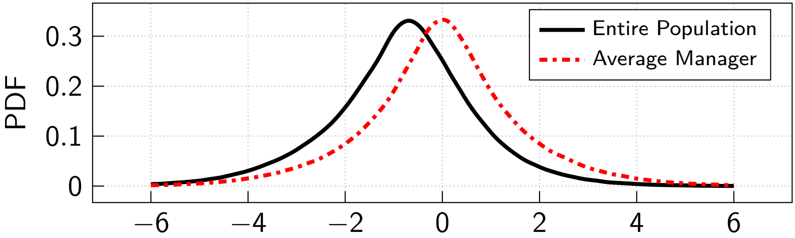

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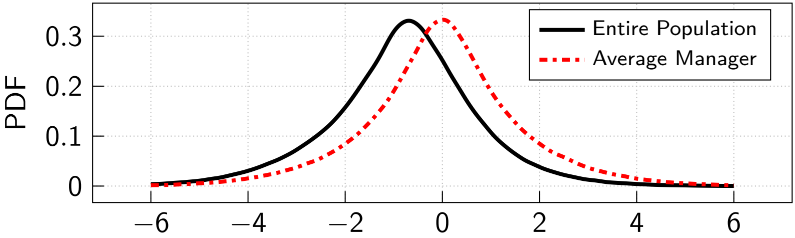
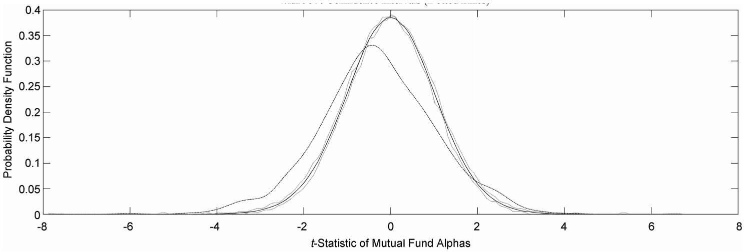
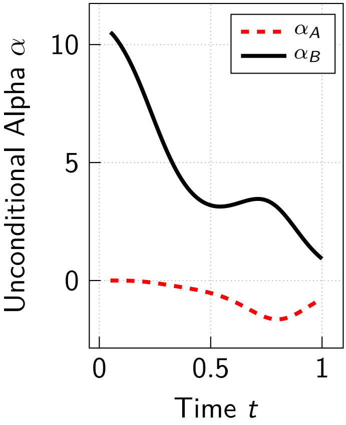




Source: Kosowski, Timmermann, Wermers & White (JF, 2006)

Persistence



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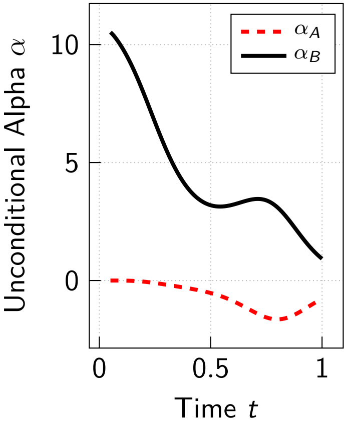

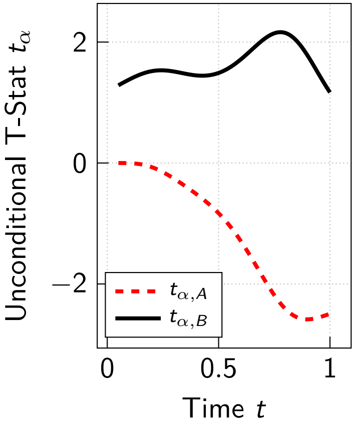

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