Social Interactions and the Performance of Mutual Funds

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A pervasive fact in the mutual fund industry

A vast literature studies the performance of mutual fund managers (e.g., Jensen (1968), Malkiel (1995), Carhart (1997), ...)

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Main Fact: Few managers generate abnormal returns and their performance does not persist.

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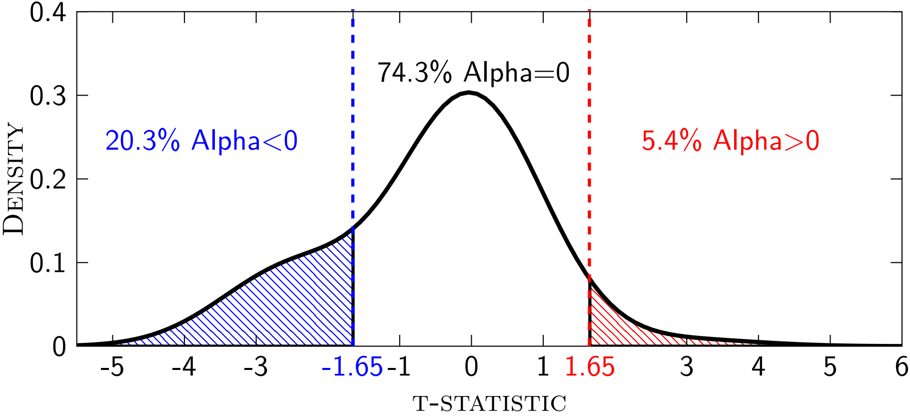
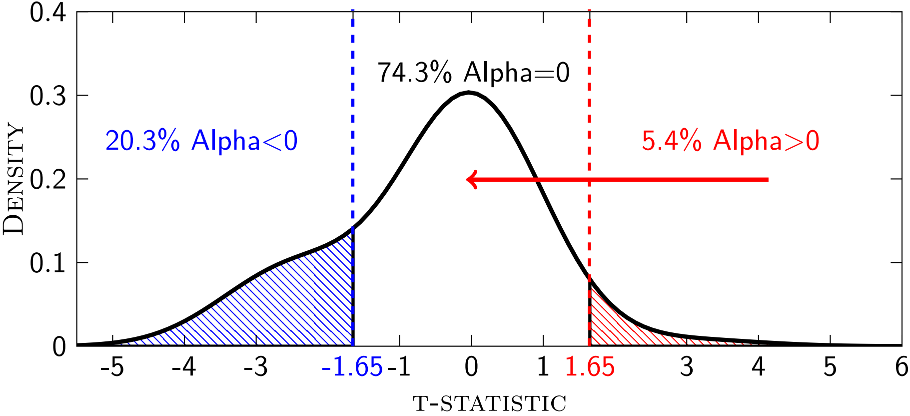


Cross-sectional distribution of alpha's t-stats

Skilled managers merely represent 2% of the population

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

A pervasive fact in the mutual fund industry

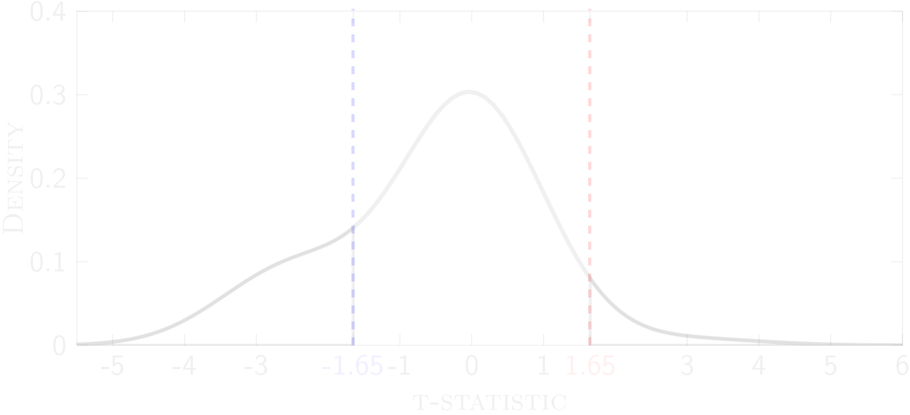


Cross-sectional distribution of alpha's t-stats

Managers do not maintain their performance

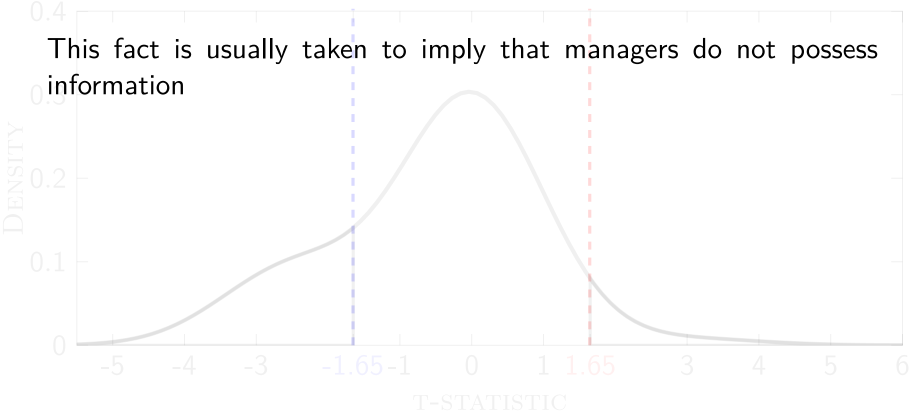
Source: Barras, Scaillet & Wermers (JF, 2010)

Puzzling Evidence



Puzzling Evidence

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



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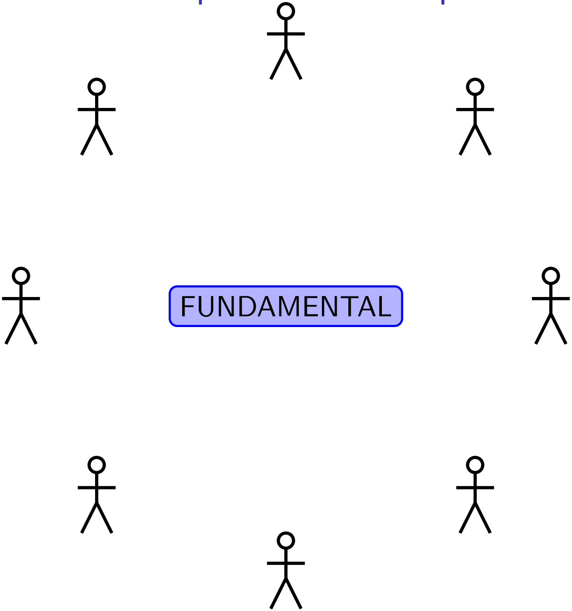
Puzzle: Strong evidence that managers do possess information e.g.:

- 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



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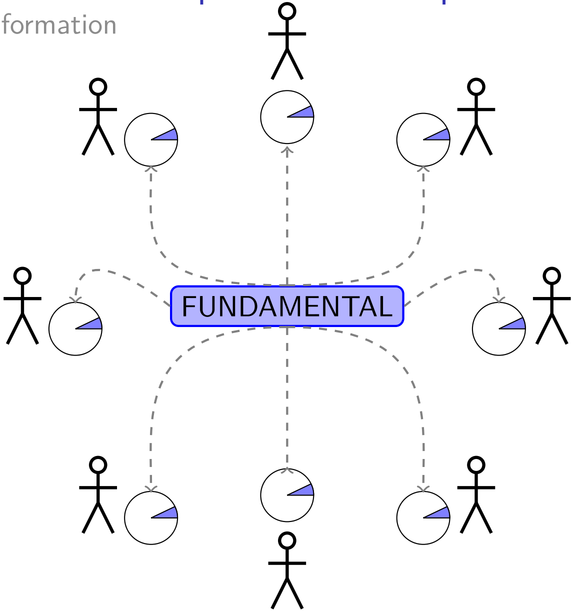
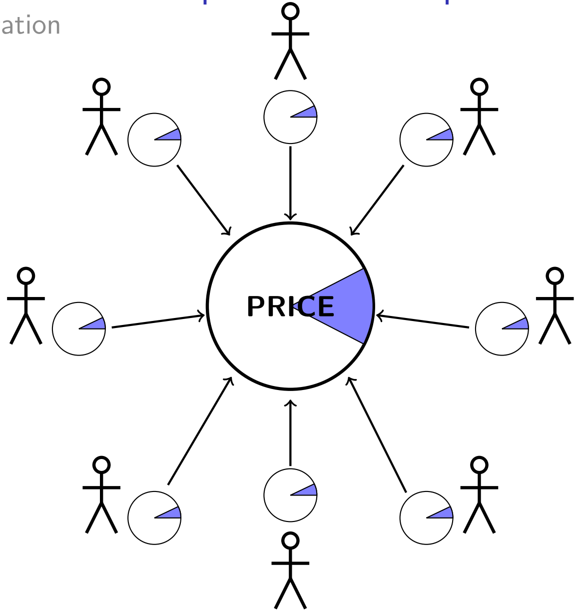
Dispersed Information



A Standard Rational-Expectations Setup

Aggregation



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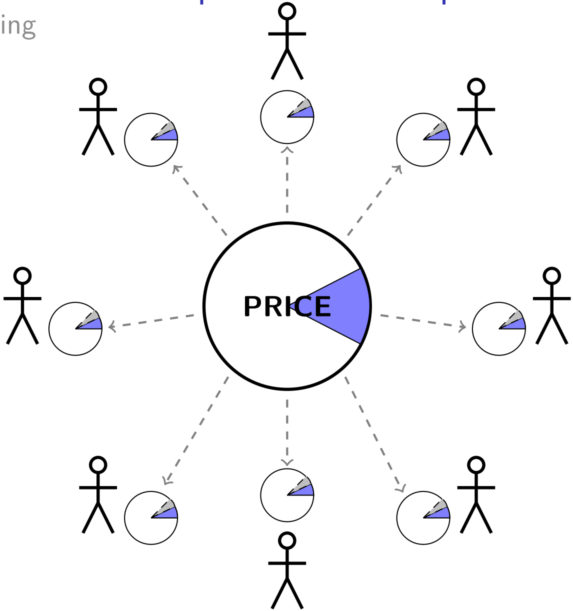
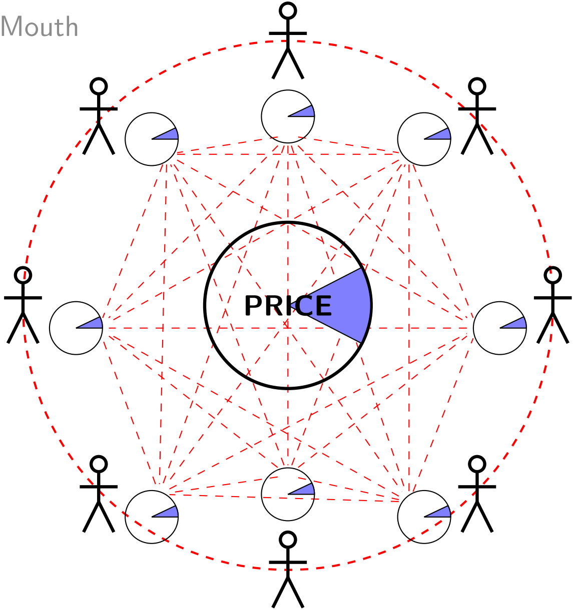
Learning



My Contribution

Word-of-Mouth



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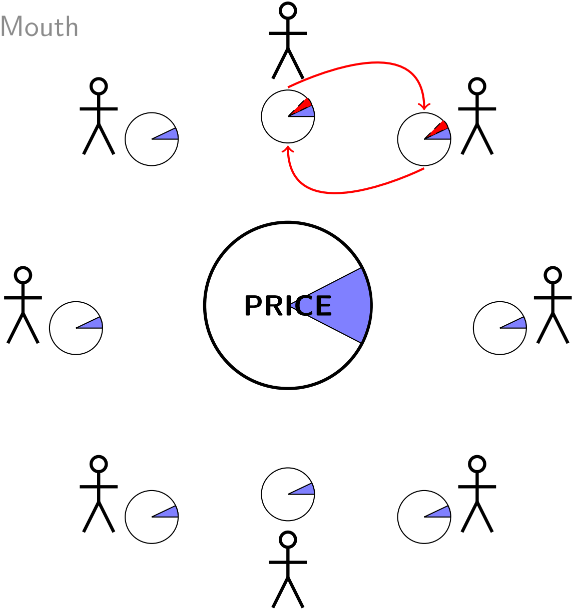

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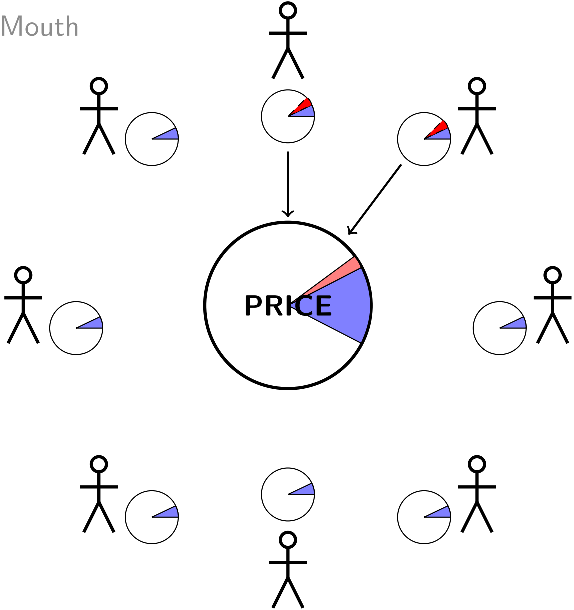

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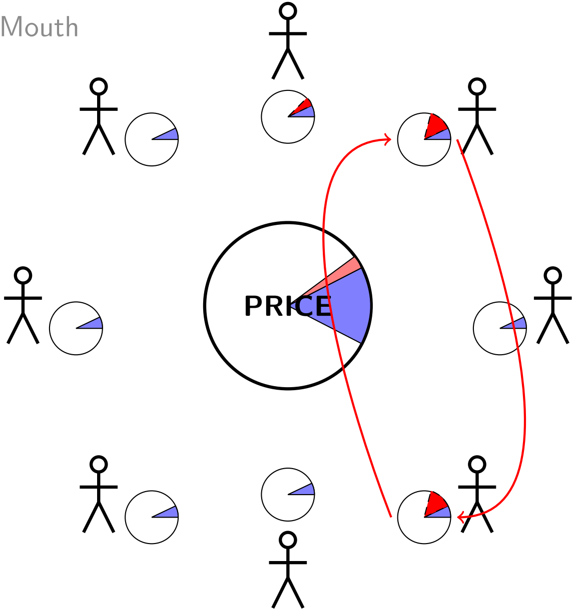

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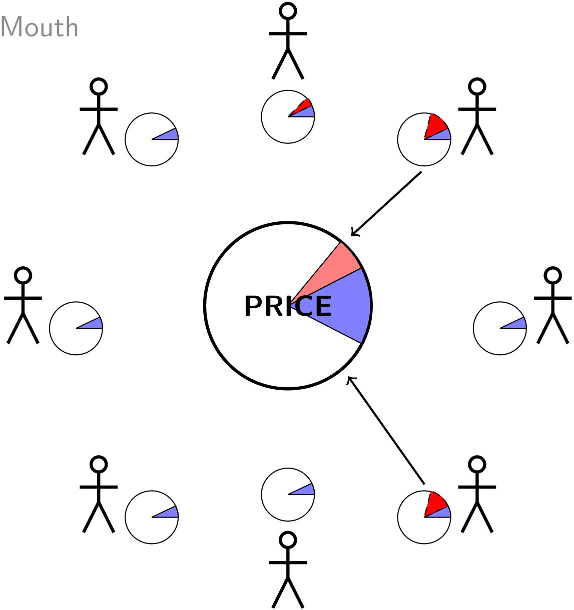

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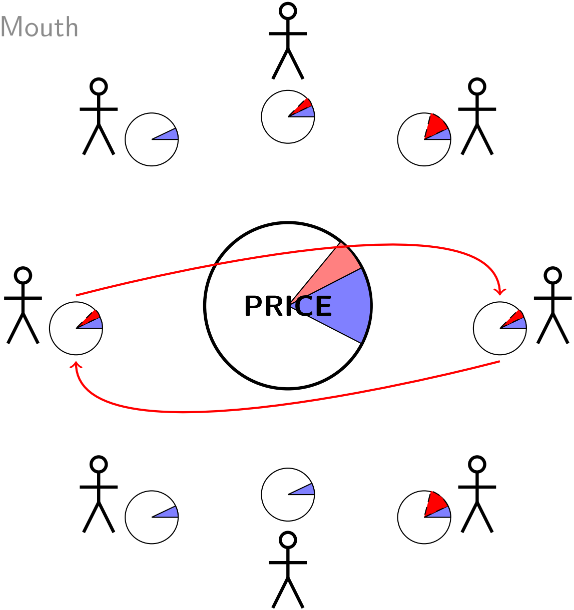

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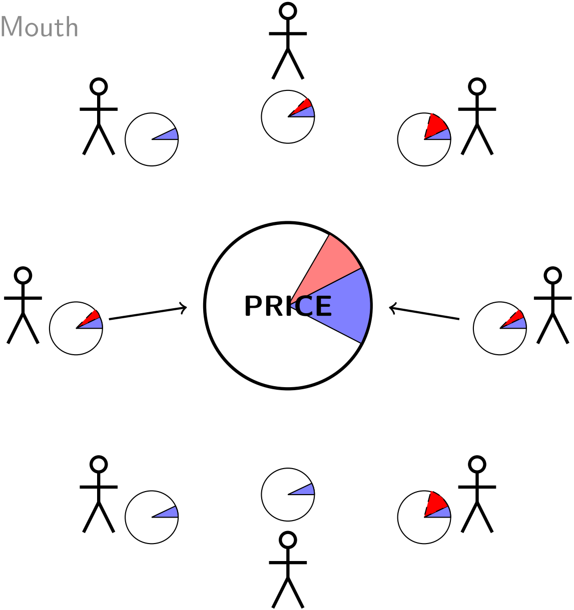

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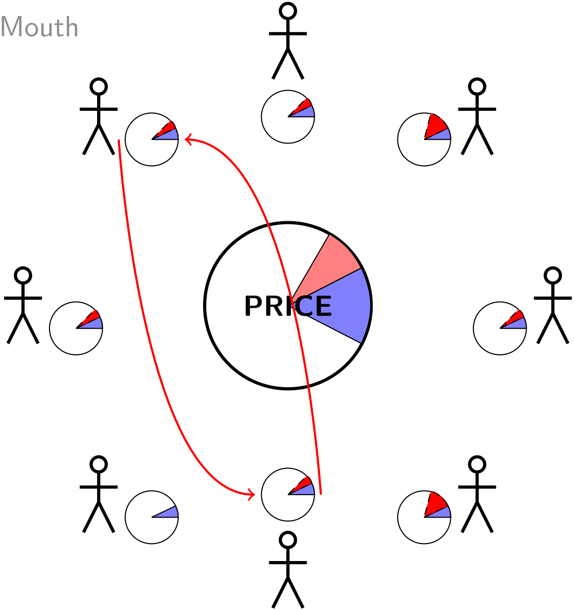

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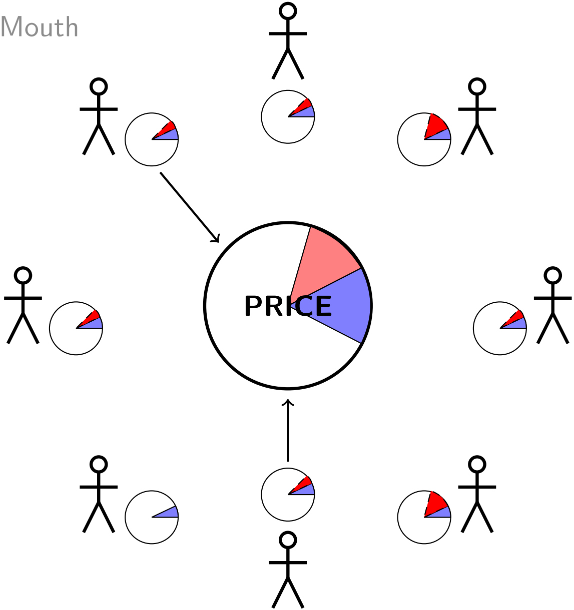

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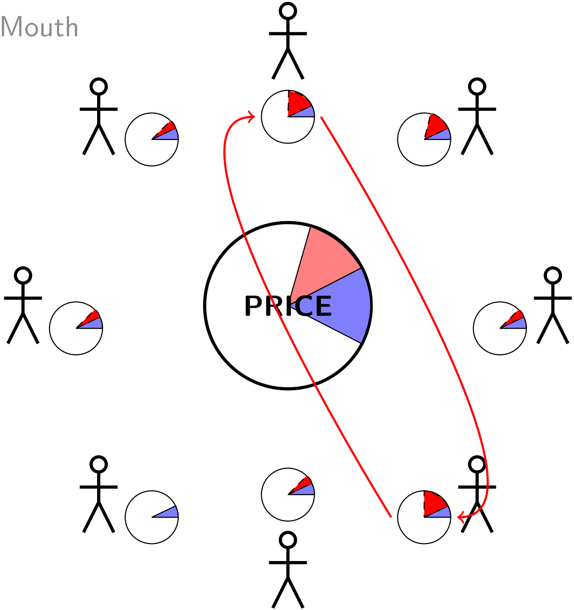

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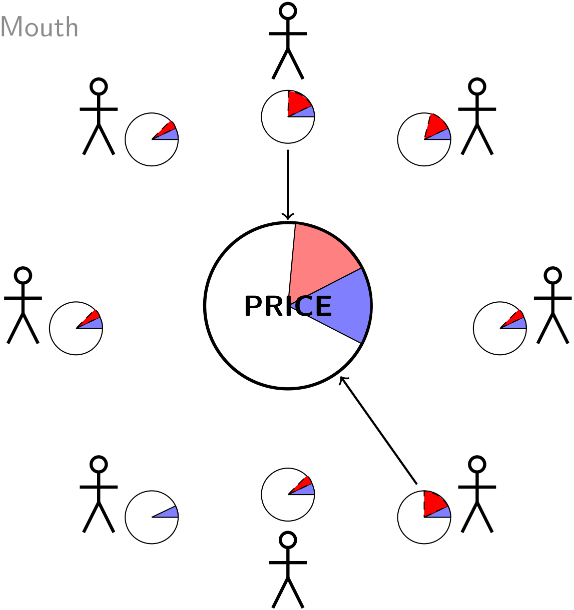

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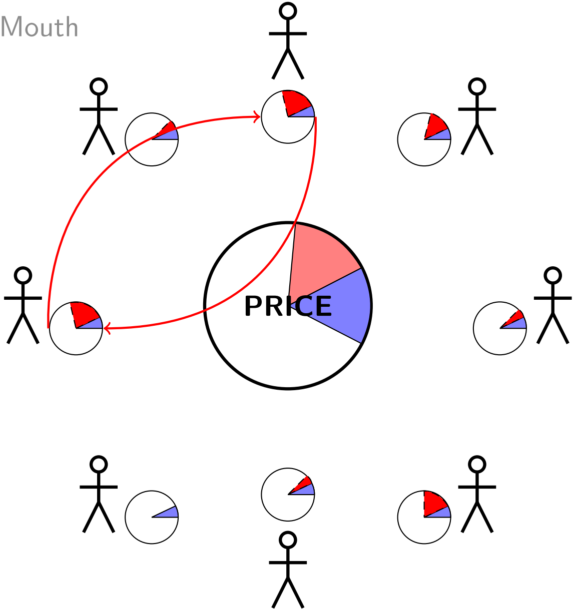

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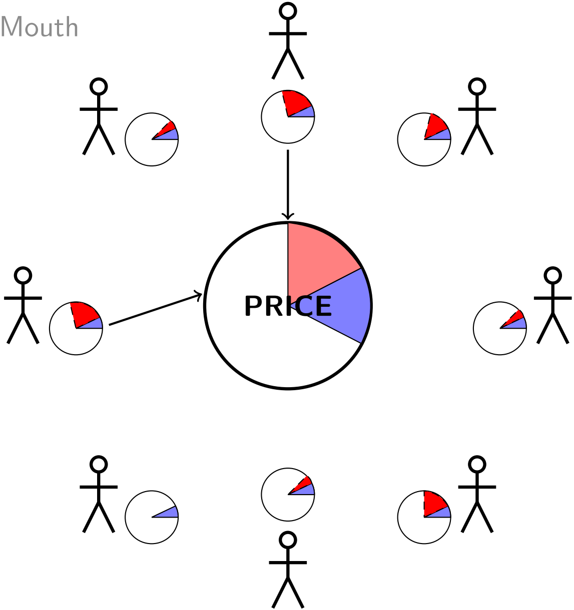

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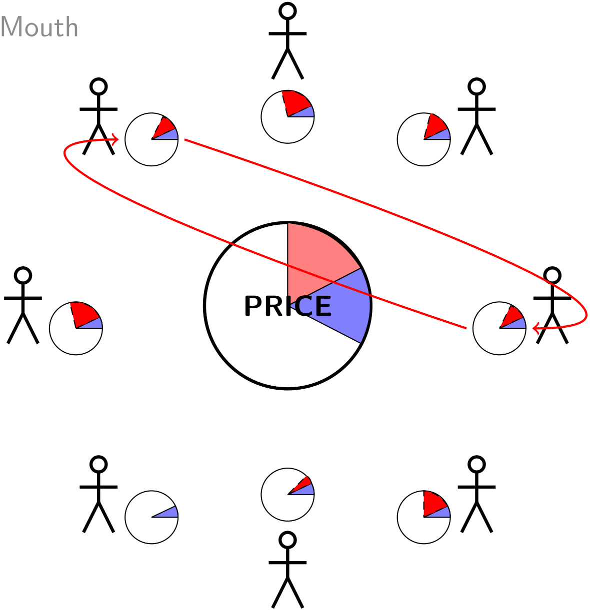

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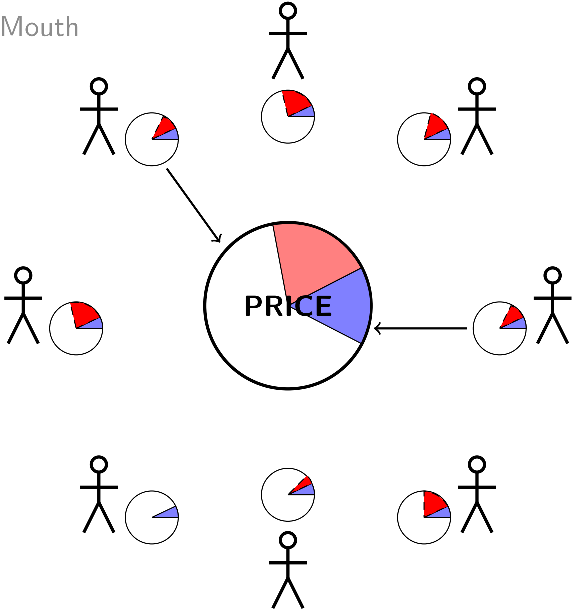

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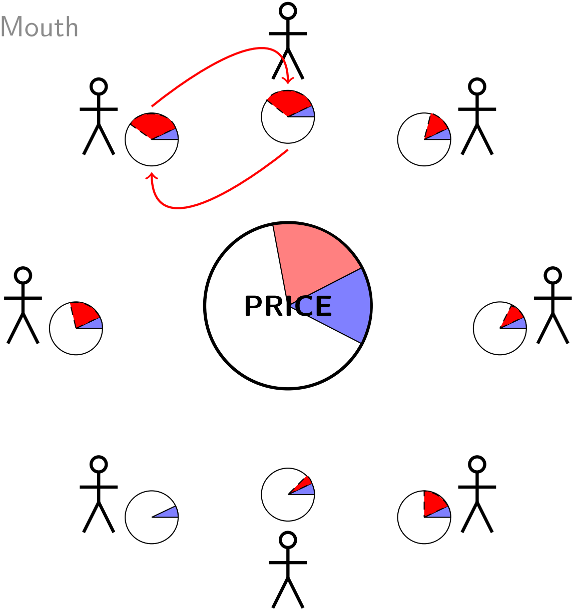

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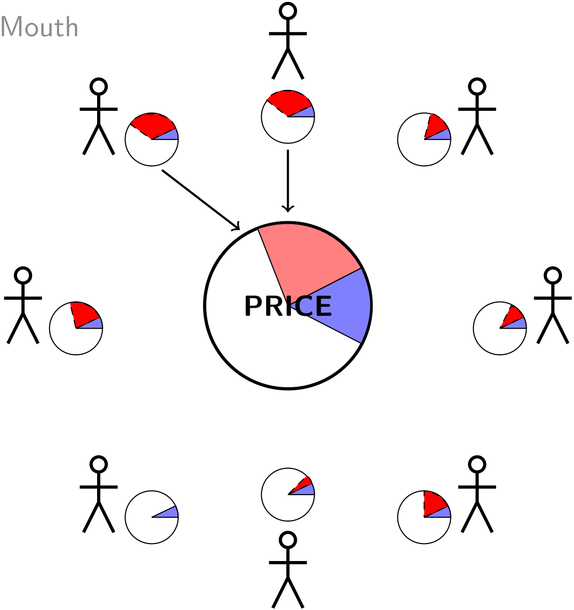
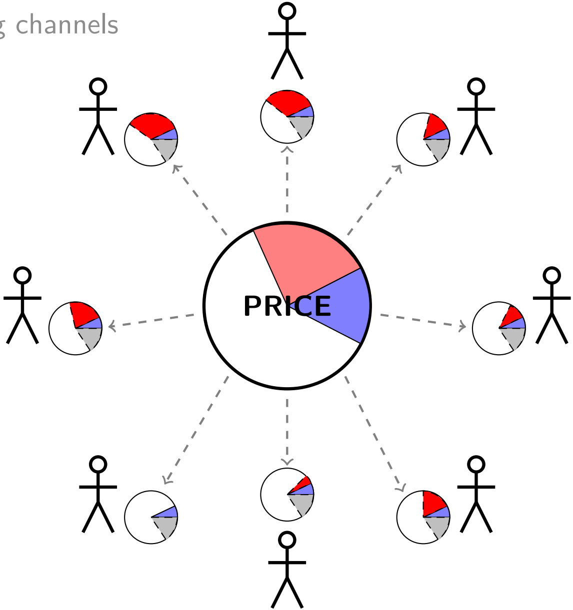


My Contribution

Two learning channels



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  - Maximal statistical significance we expect to observe?

Outline

I Model

II Solution Method

III Results

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Setup

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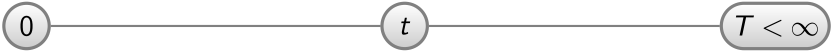
Continuous trading on $[0, T)$



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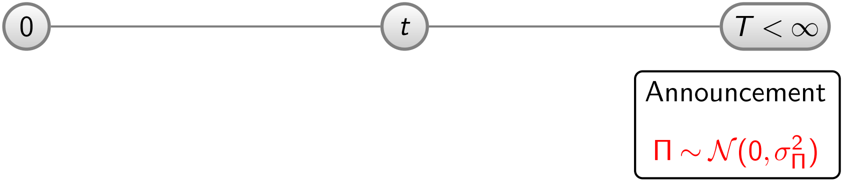

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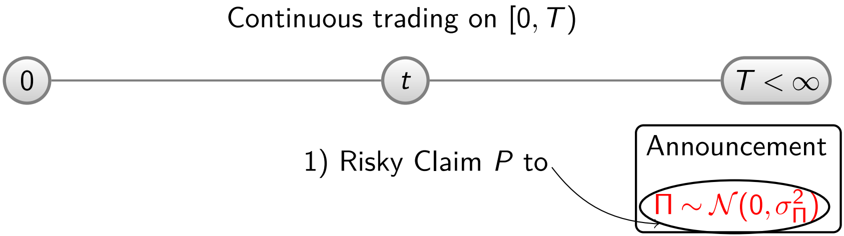
Continuous trading on $[0, T)$
0
t
$T < \infty$
1) Risky Claim P to
Announcement
$\Pi \sim \mathcal{N}(0, \sigma_\Pi^2)$

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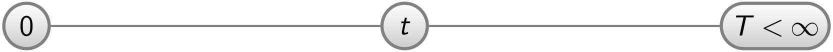

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0 — t — $T < \infty$

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

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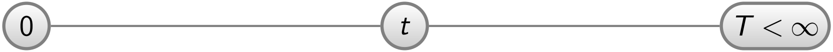

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No fund flows: managers maximize $E[U[W_T^i]|\mathcal{F}_t^i]$, $\quad i \in [0,1]$

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Noise Traders $\Longleftrightarrow$ noisy supply Θ_t

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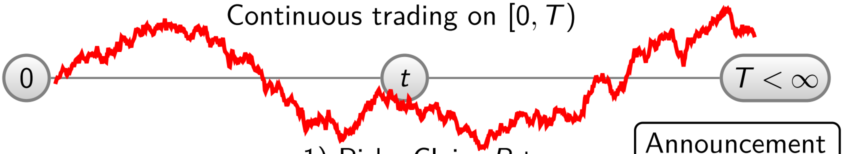

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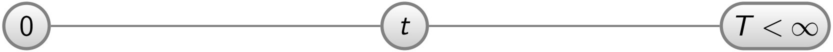
$$d\Theta_t = -a_\Theta \Theta_t dt + \sigma_\Theta dB_t^\Theta$$

Introducing Social Dynamics



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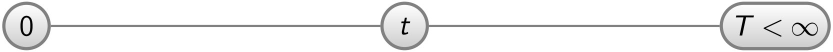

Each manager i starts with an idea $S_1^i = \Pi + \epsilon_1^i$

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

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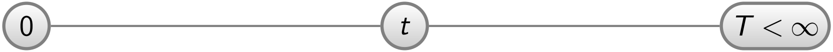

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Managers meet at Poisson random times.
Ideas percolate with intensity η_t^i.

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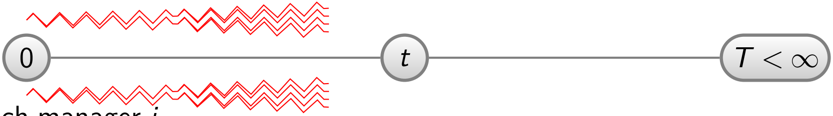

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$$\{S_j^i\}_{j=1}^3 = \{S_1^i,\ S_2^i,\ S_3^i\}$$

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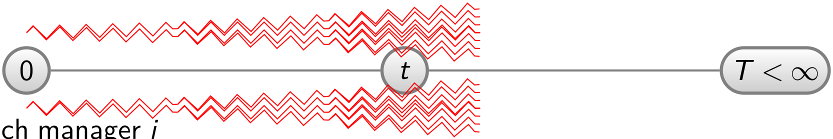

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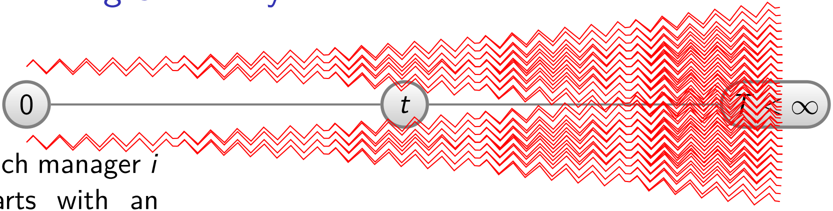

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$$\{S_j^i\}_{j=1}^{n_t} = \{S_1^i,\ S_2^i, ...,\ S_{n_t}^i\}$$

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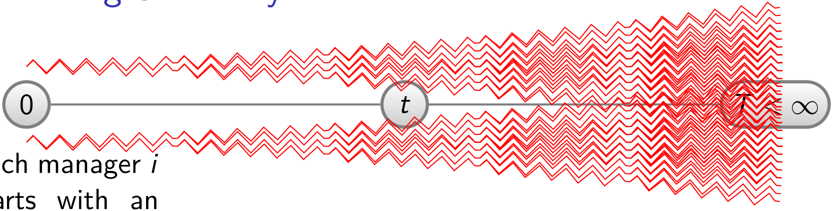

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Managers meet at Poisson random times. Ideas percolate with intensity η_t^i.

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

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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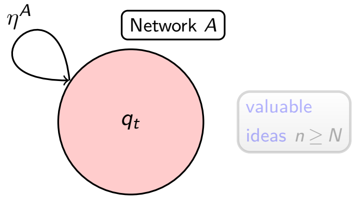

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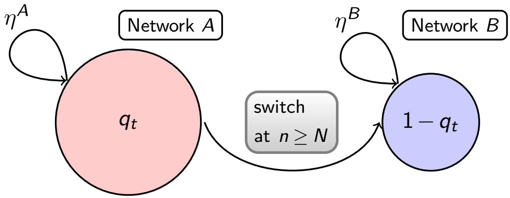

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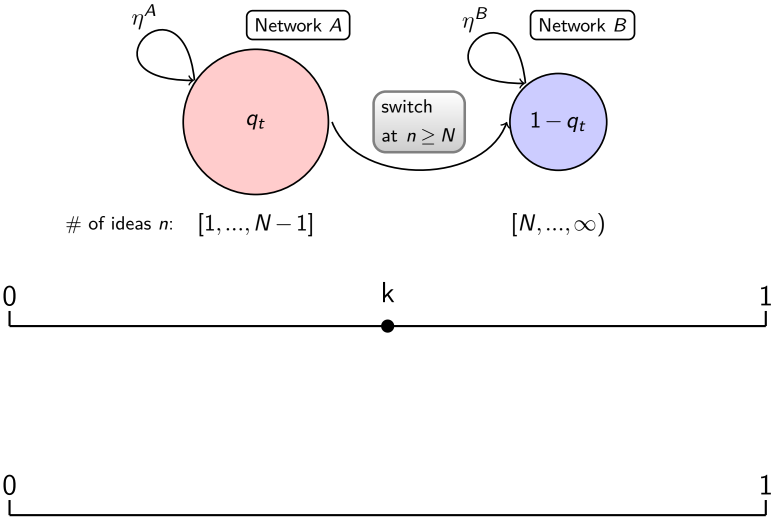

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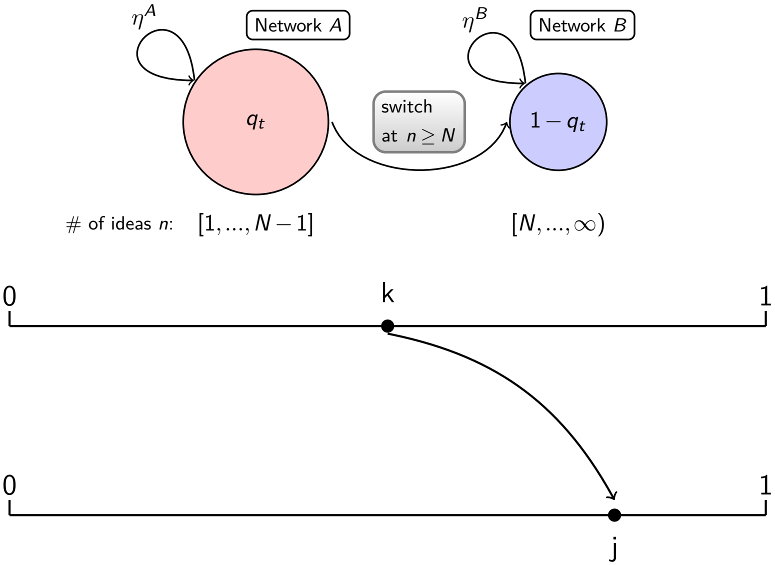

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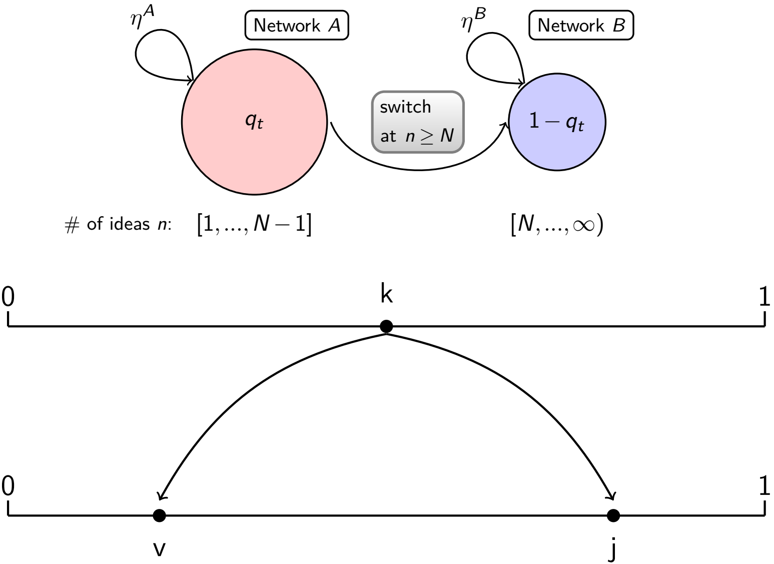

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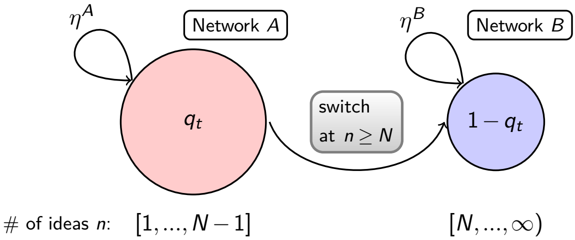

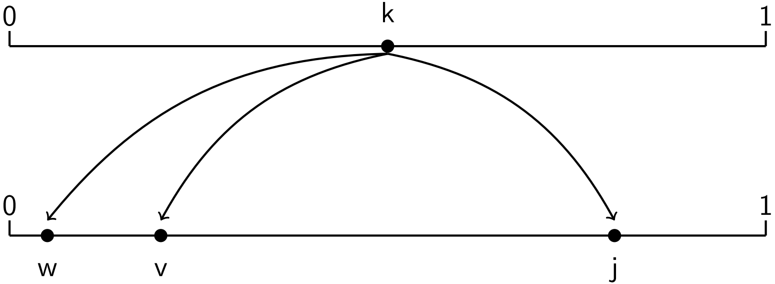

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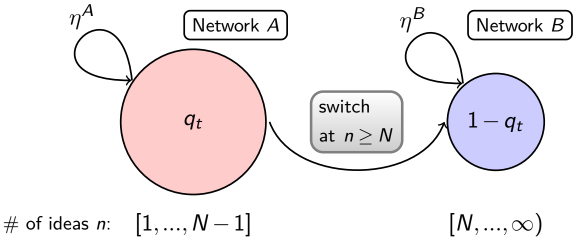

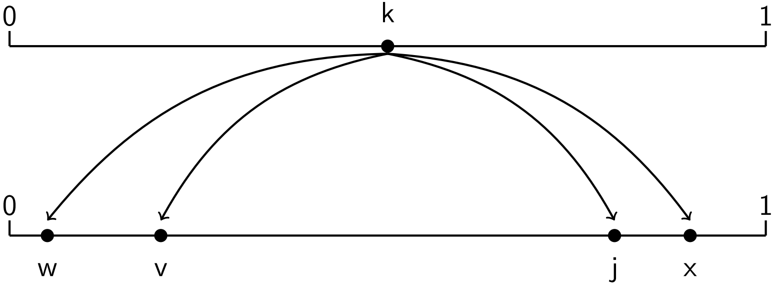

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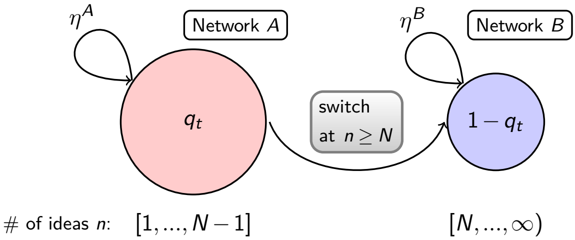

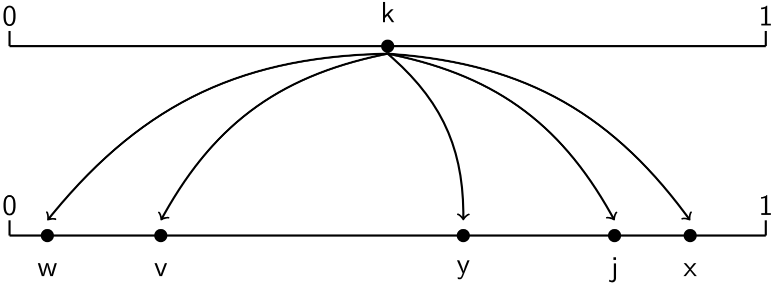

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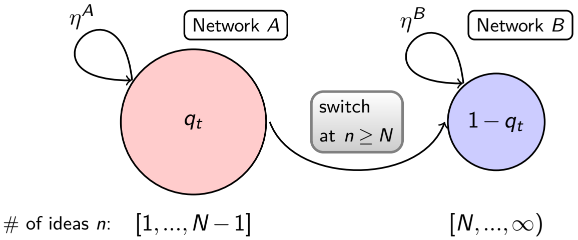
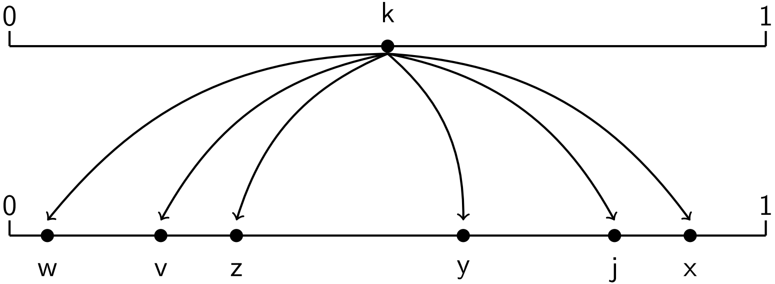
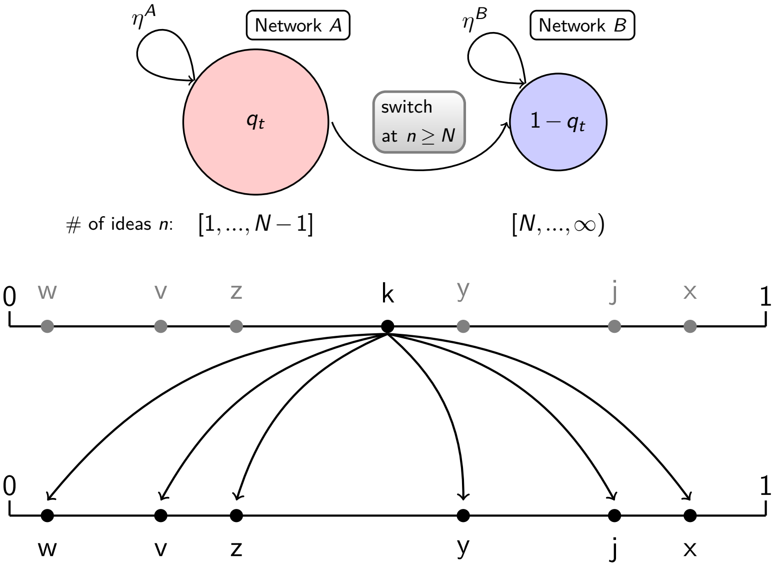




Introducing Social Dynamics



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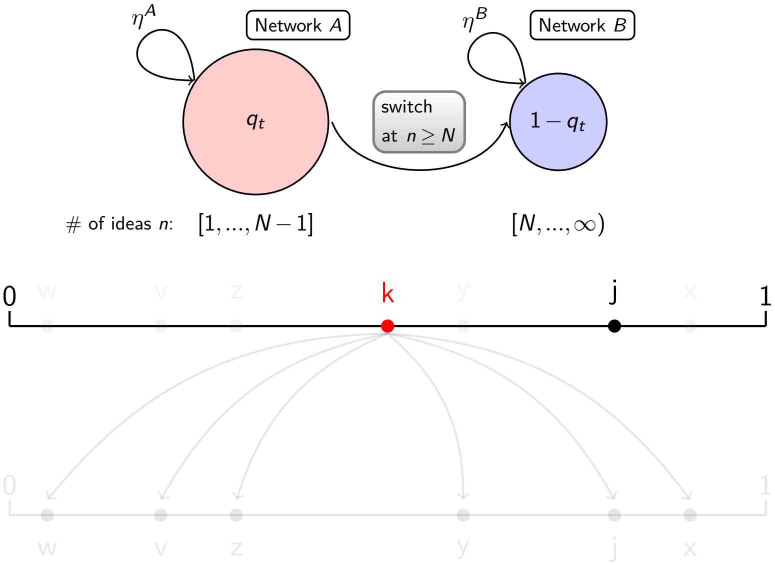

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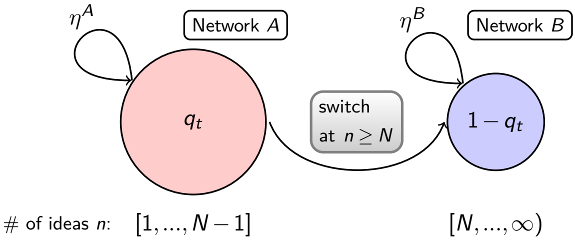
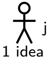
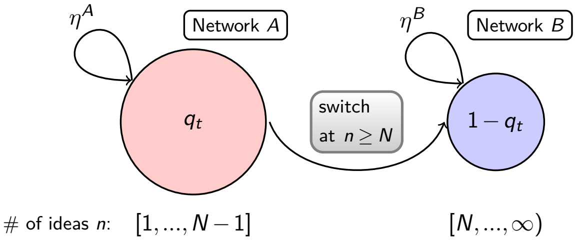
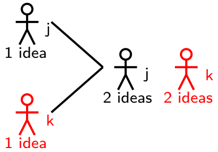




Introducing Social Dynamics





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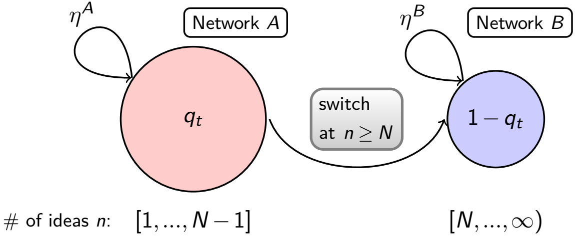

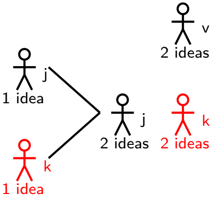

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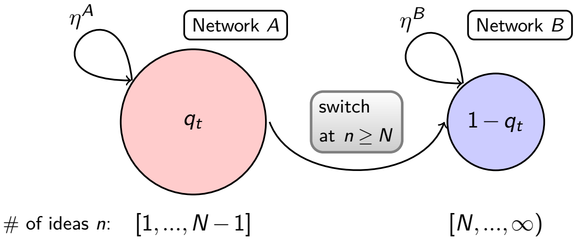

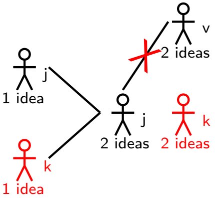

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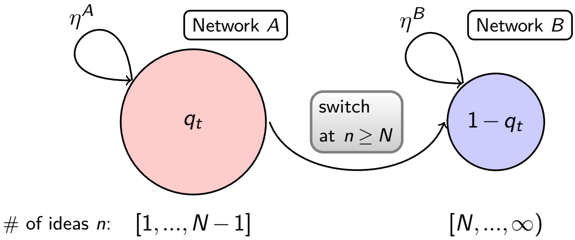

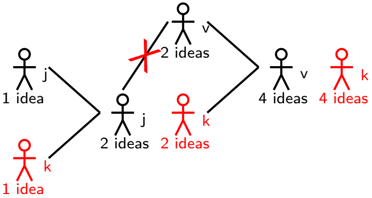

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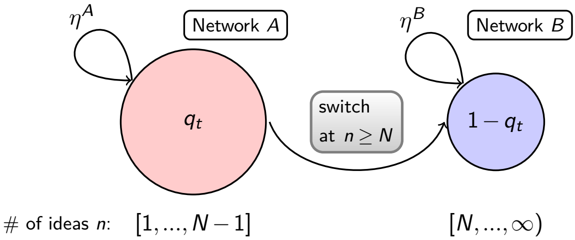

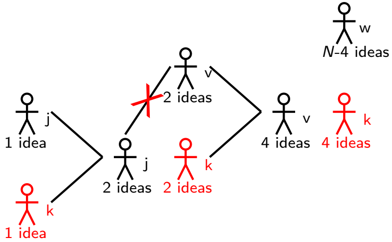

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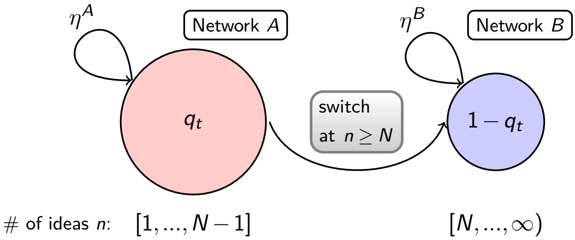

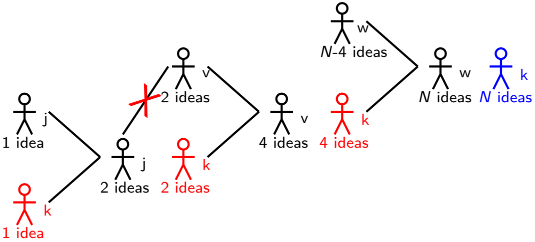

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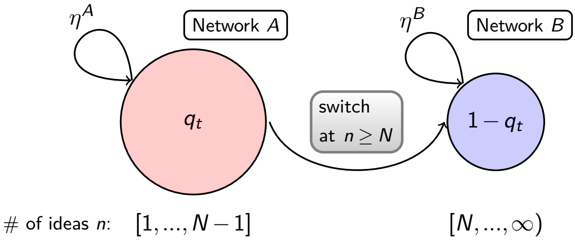

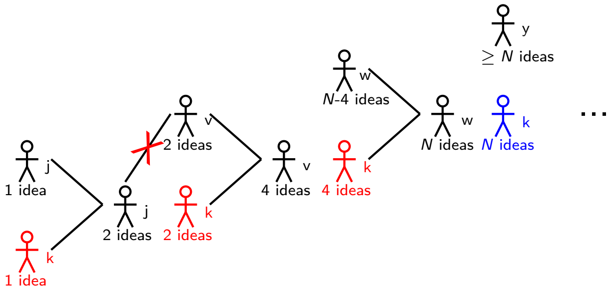

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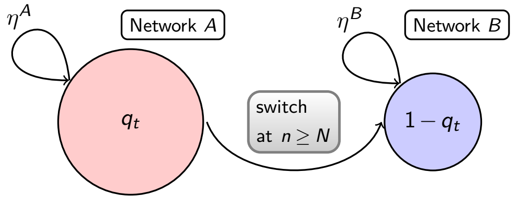


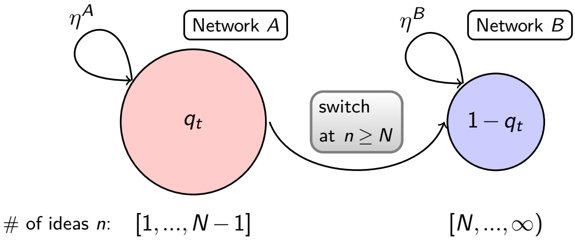
# of ideas n: $[1, ..., N-1]$ $[N, ..., \infty)$

Cross-Sectional Distribution of ideas

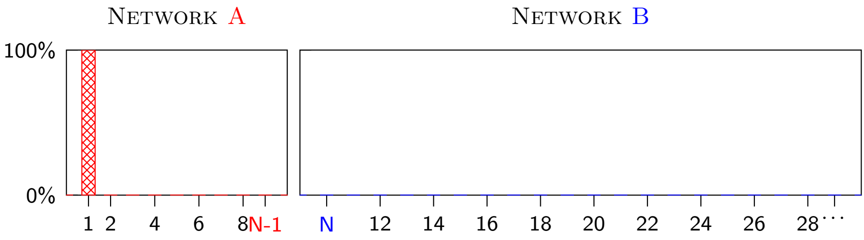
$$\frac{\mathrm{d}}{\mathrm{d}t}\mu_t(n) = \underbrace{\eta^A \mathbf{1}_{n<2N} \sum_{m=1 \vee (n-N+1)}^{(n-1)\wedge(N-1)} \mu_t(m)\mu_t(n-m) + \eta^B \mathbf{1}_{n \geq 2N} \sum_{m=N}^{n-N} \mu_t(m)\mu_t(n-m)}_{\text{Meetings}}$$

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

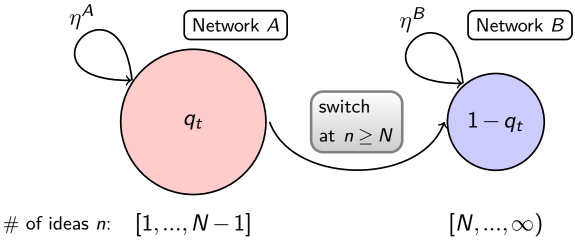
Introducing Social Dynamics



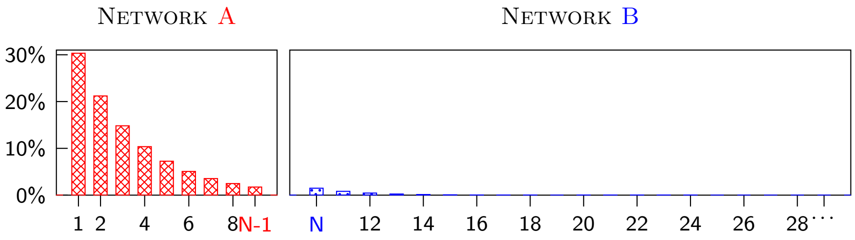
Cross-Sectional Distribution at time $t = 0$



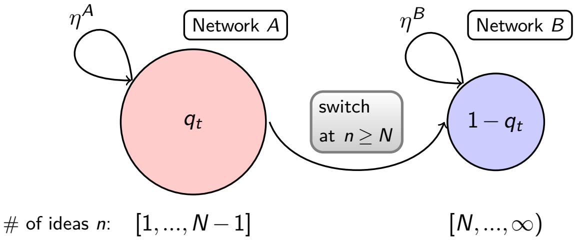
Introducing Social Dynamics



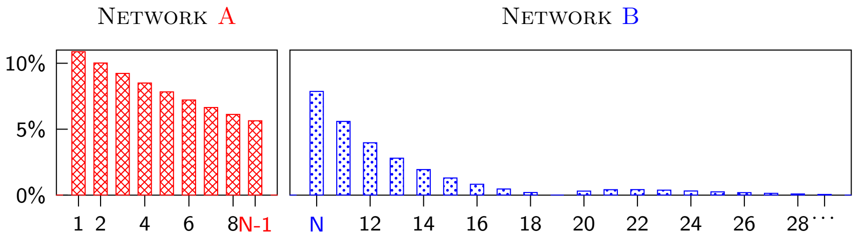
Cross-Sectional Distribution at time $t = 0.2$



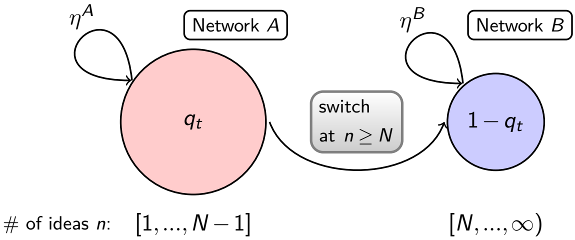
Introducing Social Dynamics



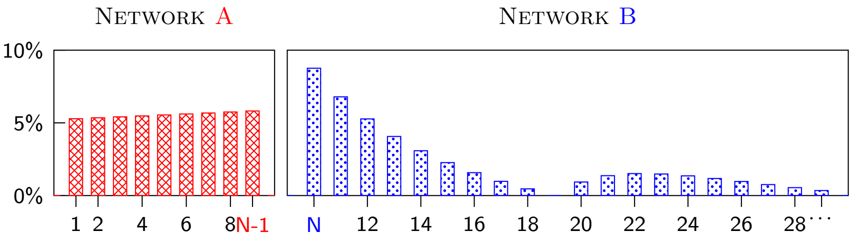
Cross-Sectional Distribution at time $t = 0.4$



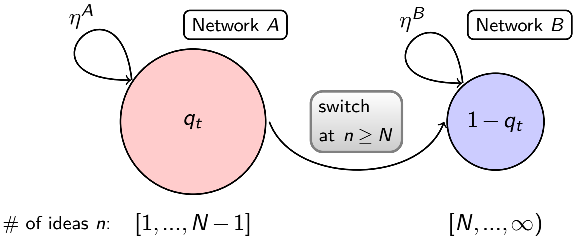
Introducing Social Dynamics



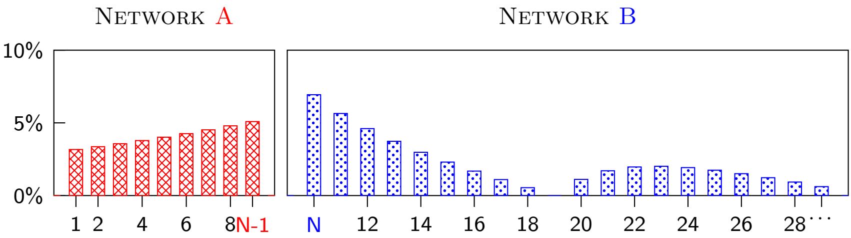
Cross-Sectional Distribution at time $t = 0.6$



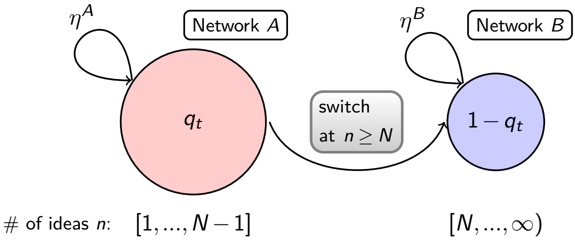
Introducing Social Dynamics



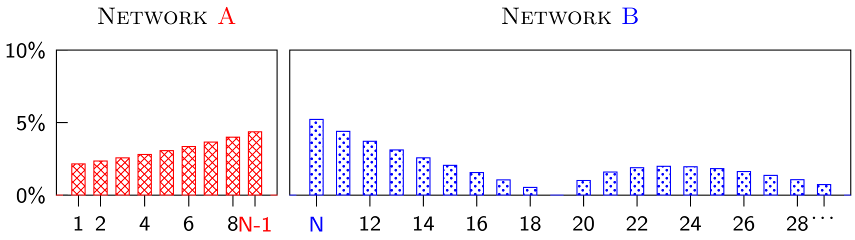
Cross-Sectional Distribution at time $t = 0.8$



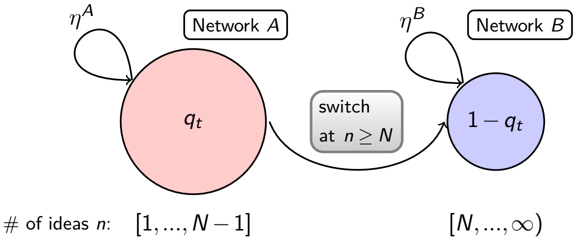
Introducing Social Dynamics



Cross-Sectional Distribution at time $t = 1$



Introducing Social Dynamics

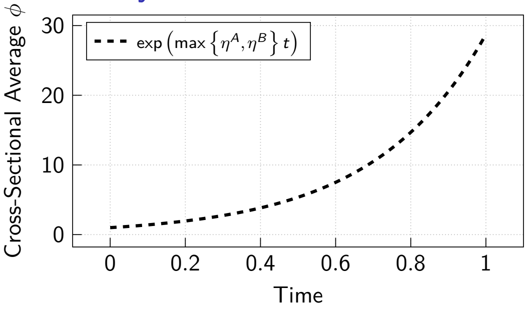


Cross-Sectional Average Number of ideas

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

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

Introducing Social Dynamics

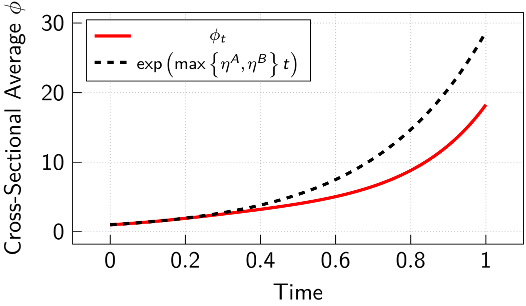


Cross-Sectional Average Number of ideas

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

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

Introducing Social Dynamics



Cross-Sectional Average Number of ideas

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

Outline

Steps (He and Wang (1995))

1. Price Conjecture

4. Market Clearing

2. Learning Process

3. Individual Optimization

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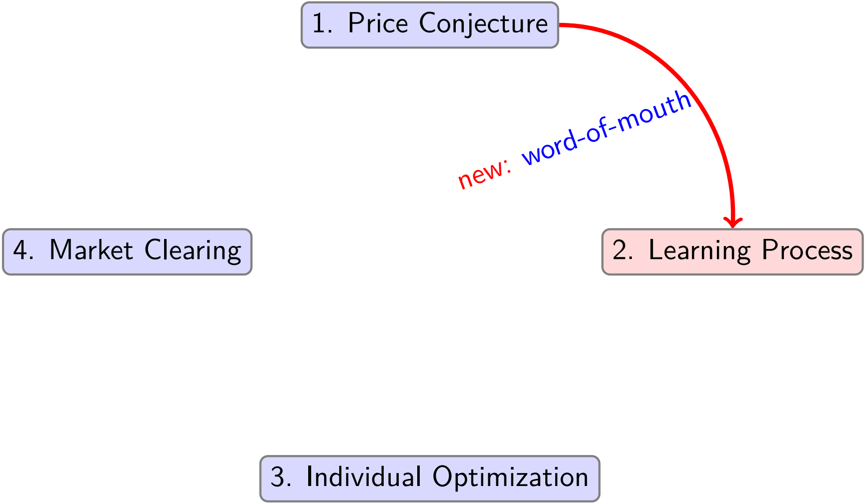

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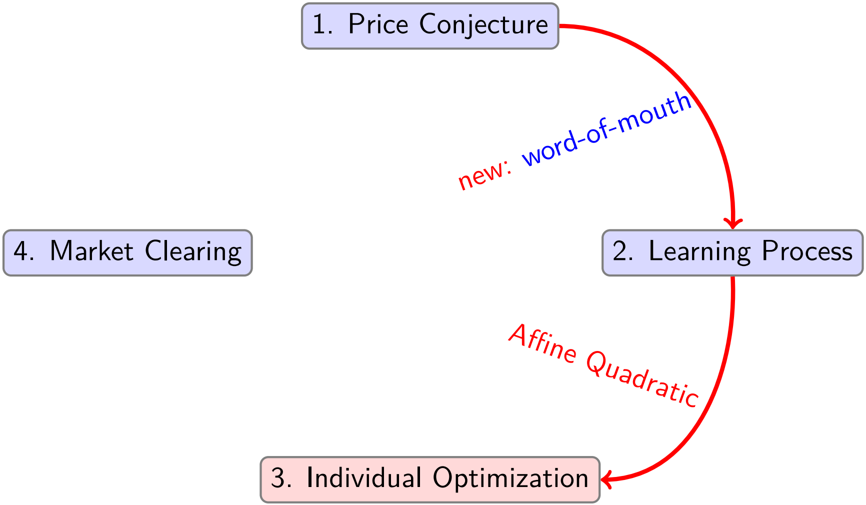
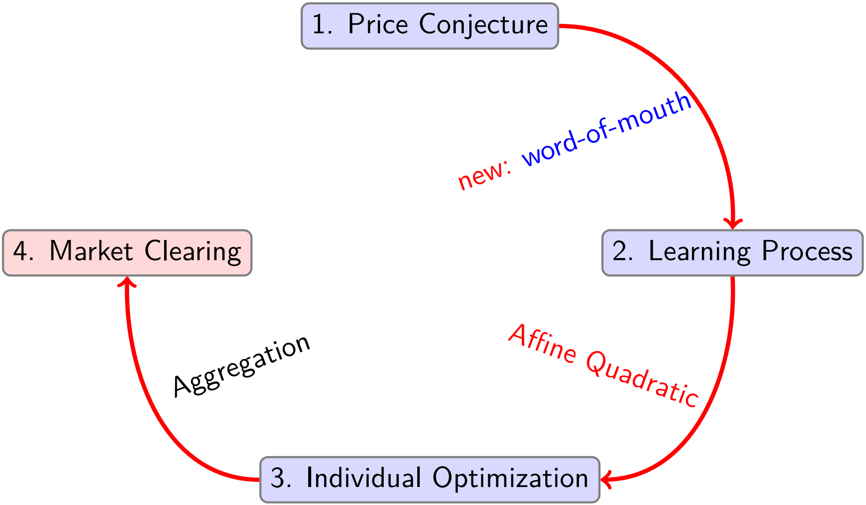
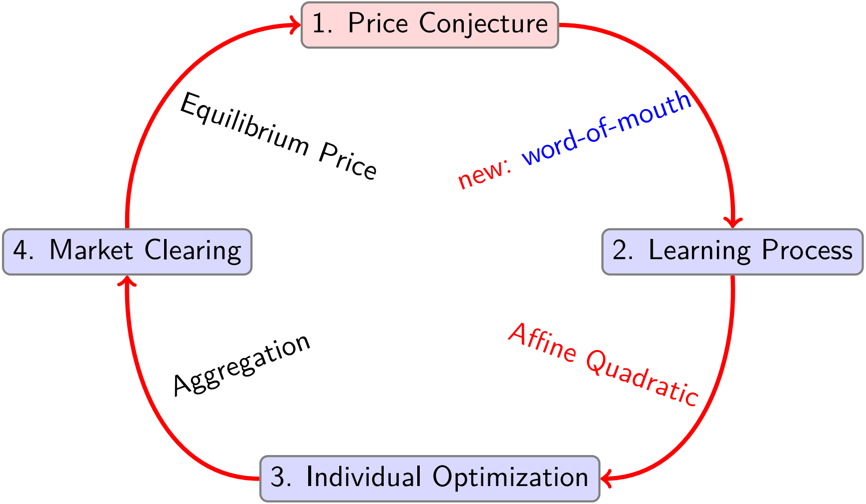


Steps (He and Wang (1995))



Steps (He and Wang (1995))



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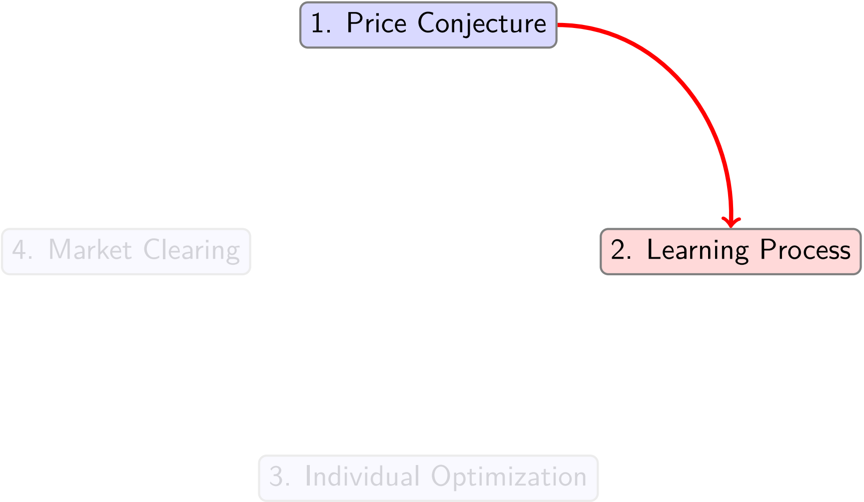

Word-of-Mouth Learning

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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WATCHING THE TAPE

MEETINGS

Word-of-Mouth Learning

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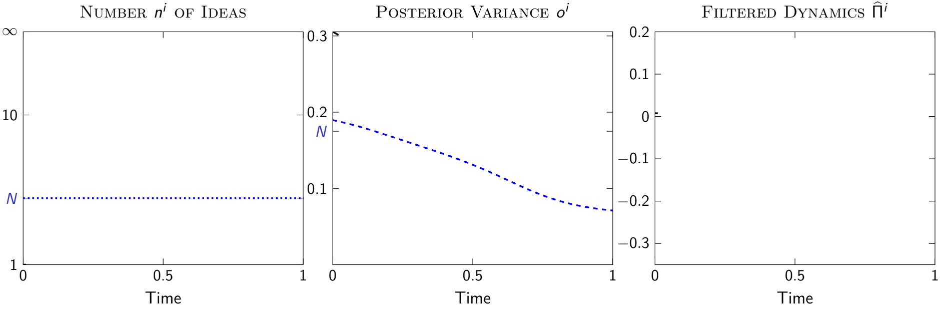

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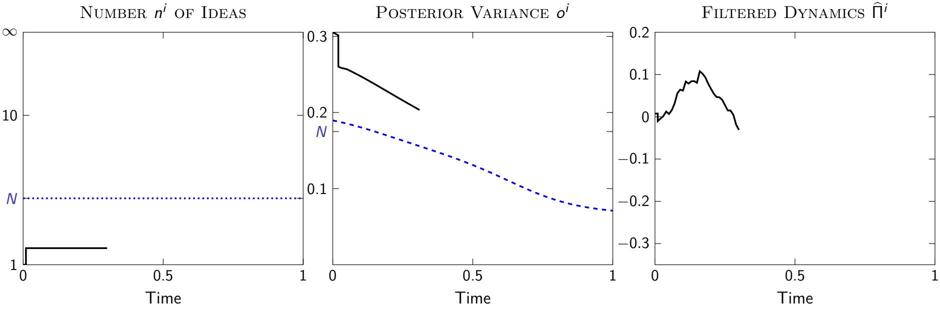

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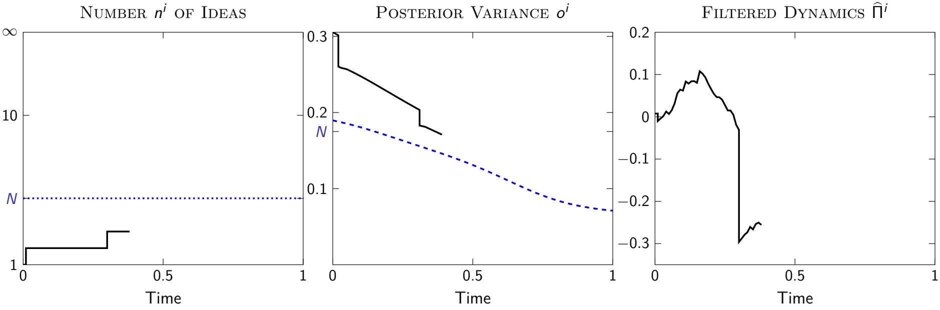

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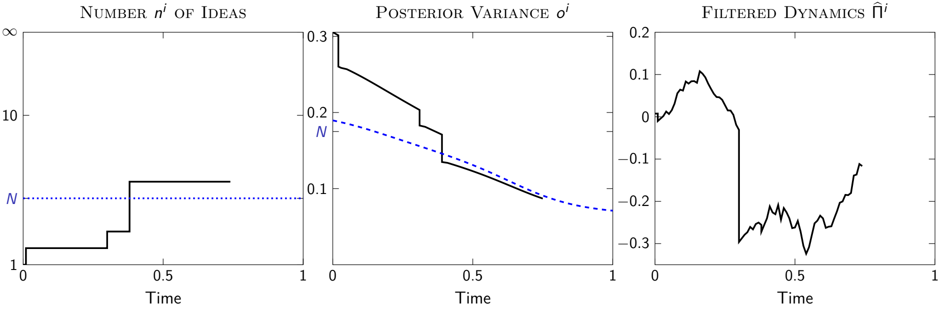

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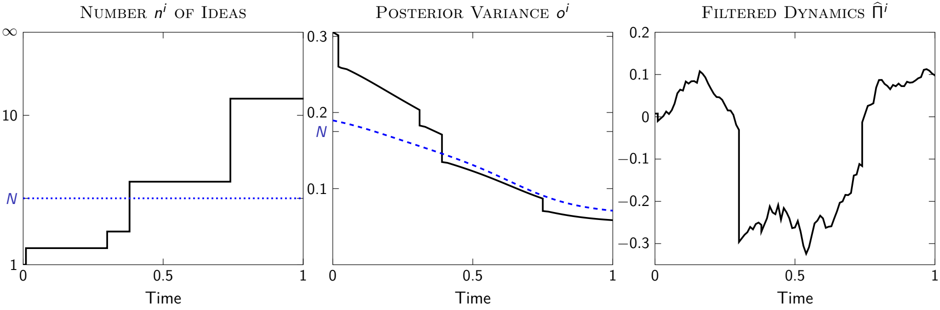
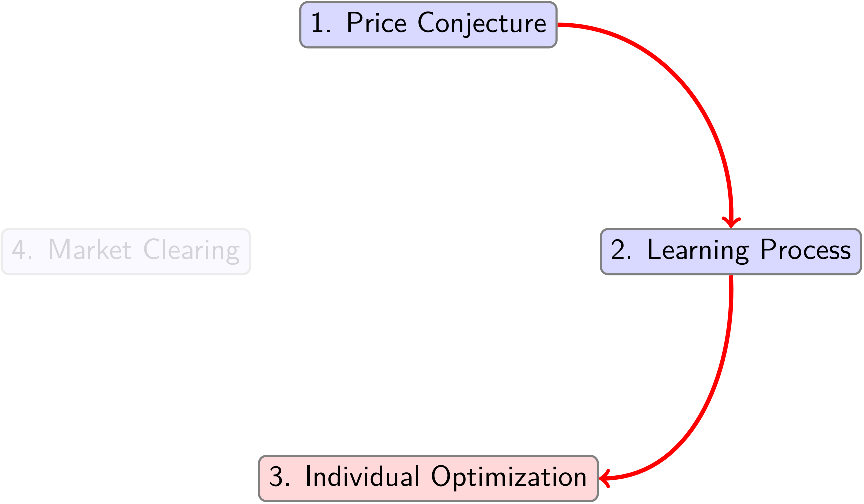


Steps (He and Wang (1995))



Social Interactions Increase Trading Aggressiveness

A manager i builds an optimal portfolio θ^i:

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

$$= \underbrace{d_{\Theta,t}(n^i)\left(\Theta_t - \frac{\lambda_{1,t}}{\lambda_{2,t}}(\widehat{\Pi}^i - \Pi)\right)}_{\text{Market-Making Position}} + \underbrace{d_{\Delta,t}(n^i)\left(1 - \frac{o_t(n^i)}{o^c_t}\right)(Y^i - \widehat{\Pi}^c)}_{\text{Speculative Position}}$$

$$= \underbrace{d_{\Theta,t}(n^i)\Theta_t}_{\text{Per-Capital Supply Shocks}} + \underbrace{\tilde{\theta}^i_t}_{\text{Informational Position}}$$

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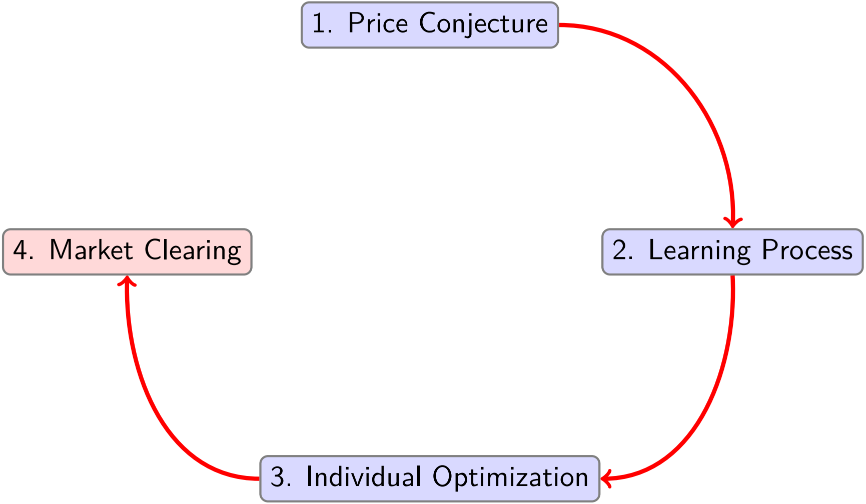
$$\equiv \underbrace{d_{\Theta,t}(n^i)\Theta_t}_{\text{Per-Capital Supply Shocks}} + \underbrace{\widehat{\theta}_t^i}_{\text{Informational Position}}$$

Steps (He and Wang (1995))



A Zero-Sum Game Among Managers

The market-clearing condition implies

$$\underbrace{\int_{i\in I}\widehat{\theta}_t^i \mathrm{d}\iota(i)}_{\substack{\text{Informational Trading} \\ \equiv 0}} + \Theta_t \underbrace{\int_{i\in I} d_{\Theta,t}(n_t^i)\mathrm{d}\iota(i)}_{\substack{\text{Market Making} \\ \equiv 1}} = \Theta_t.$$

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a perfectly informed manager trades on information only

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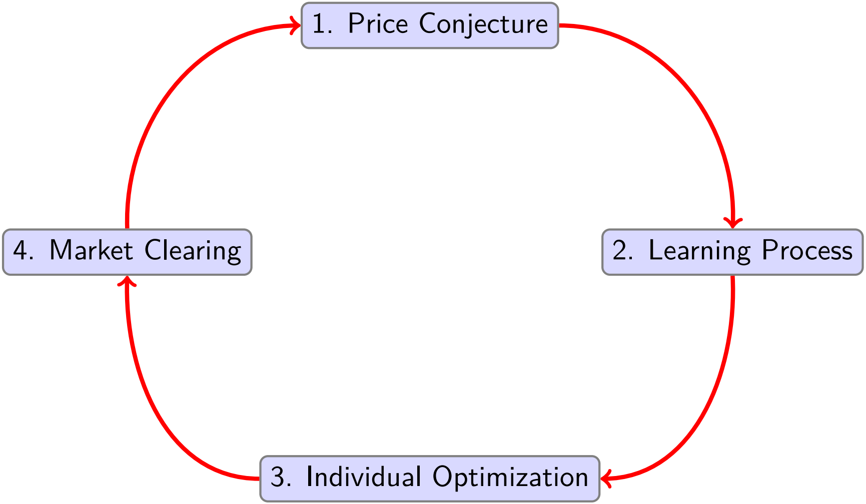
the average manager ($n^i \equiv \phi$) trades on noise only

Steps (He and Wang (1995))



Price Informativeness

The cross-sectional average ϕ_t drives the informativeness of the equilibrium price signal

$$\xi_t = \underbrace{\frac{\phi_t}{\gamma \sigma_S^2}}_{\text{signal-noise ratio}} \Pi - \Theta_t$$

and common uncertainty $o_t^c = \left(\frac{1}{\sigma_\Pi^2} + \frac{1}{\gamma^2 \sigma_S^4} \int_0^t \left(\frac{\mathrm{d}}{\mathrm{d}s} \phi_s \right)^2 \mathrm{d}s \right)^{-1}$.

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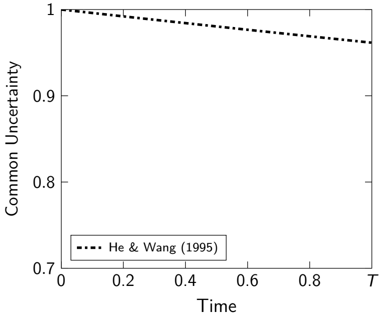

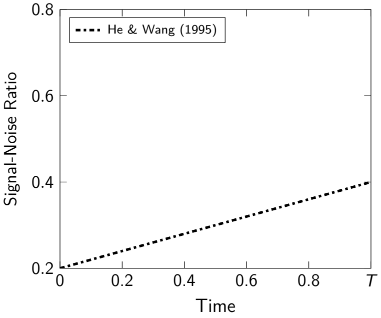

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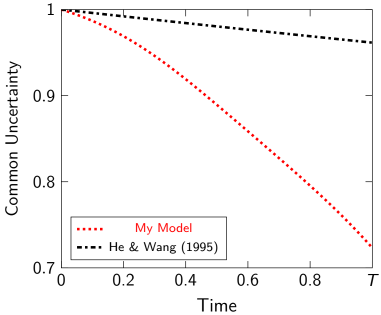

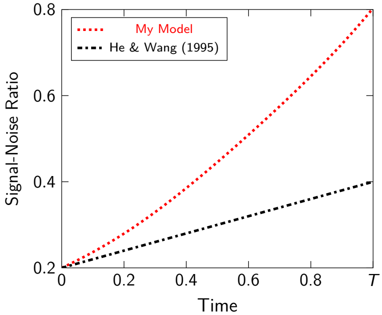

Outline

Informational Alpha Estimation

Assumption

The econometrician observes the time series of returns $(\widehat{\theta}_t^i dP_t)_{t \geq 0}$ *that a manager generates based on her informational position.*

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Informational Alpha is a Noisy Measure of Skill

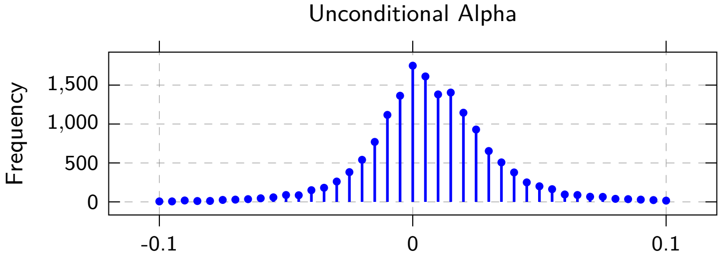
The unconditional instantaneous estimate, $\widehat{\alpha}_t^i$, of manager i's alpha is

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

Its unconditional instantaneous standard error, $\sigma_{\alpha,t}^i$, is given by

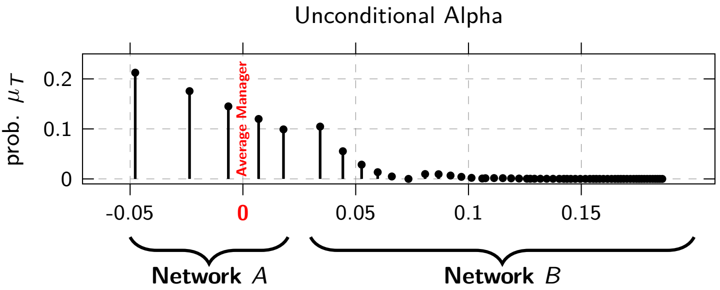
$$\sigma_{\alpha,t}(n^i) = \underbrace{\frac{\sigma_S^2(|k_t| + \gamma\sigma_\Theta)o_t^c}{\sigma_S^2 + o_t^c\phi_t}}_{\text{Market Volatility}}\sqrt{\underbrace{a_t(n^i)^2\mathbb{E}[\Delta_t^2]}_{\text{Fundamental Risk}} + \underbrace{b(n^i)^2}_{\text{Idiosyncratic Risk}}}.$$

Social Network Calibration (GMM)



Parameter	**Symbol**	**Value**
Network Threshold	N	6^{***} (0.600)
Meeting Intensity A	η^A	1.679^{***} (0.087)
Meeting Intensity B	η^B	3.806^{***} (0.583)

Cross-Sectional Performance



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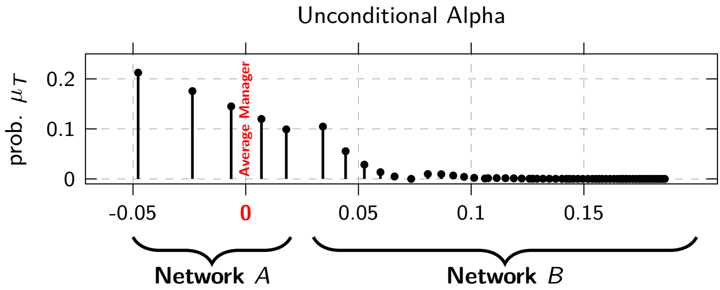
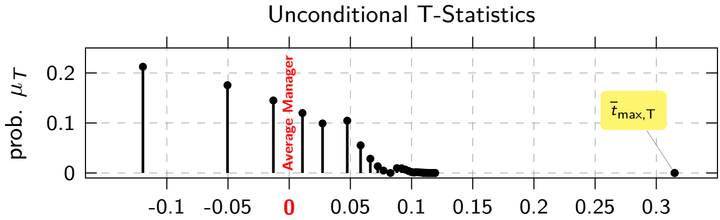
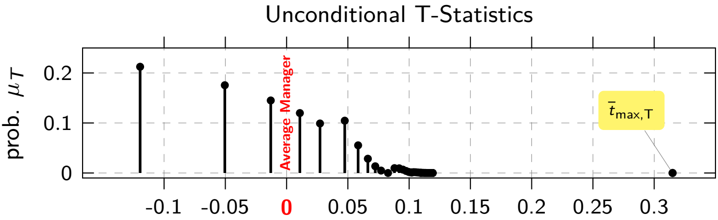




Cross-Sectional Performance

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

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



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1. Consider first a standard REE with a Brownian flow of information (He and Wang (1995) in continuous time):

$$dS_t^i = \Pi dt + \sigma_S dB_t^i.$$

The average rate of information arrival is $\phi_t = t$ and is identical for all manager, and

$$t_{max,t} = \sqrt{\frac{2}{\pi}} \frac{\sigma_\Pi}{\sqrt{\gamma^2 \sigma_S^4 \sigma_\Theta^2 + \sigma_\Pi^2 t}}.$$

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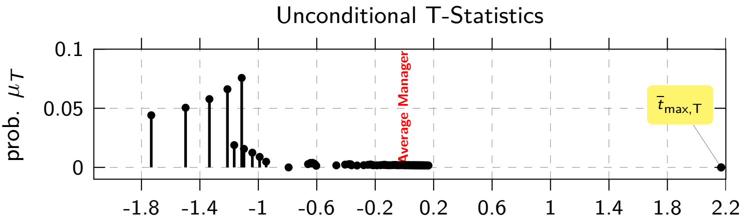
Cross-Sectional Performance



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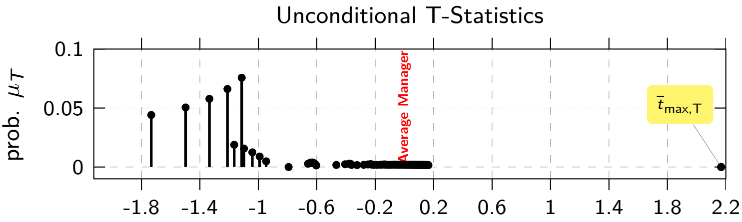

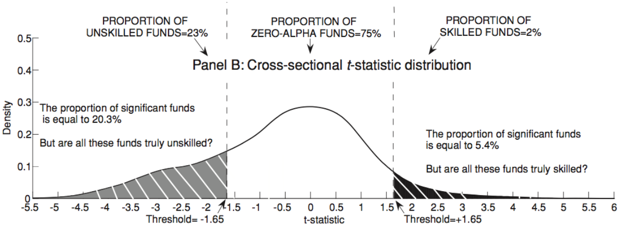

Source: Barras, Scaillet & Wermers (JF, 2010)

The Role of Luck

A manager's conditional alpha satisfies

$$\alpha_t^i = \frac{\sigma_S^4 k_t (k_t - \gamma \sigma_\Theta) o_t^c}{(\sigma_S^2 + o_t^c \phi_t)^2} \left(\underbrace{a_t(n_t^i)(\Delta_t^2 + \gamma o_t^c \Theta_t \Delta_t)}_{\text{Skill}} + \underbrace{b(n_t^i)(\Delta_t + \gamma o_t^c \Theta_t)\epsilon_t^i}_{\text{Luck}} \right).$$

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The perfectly informed manager trades on skill

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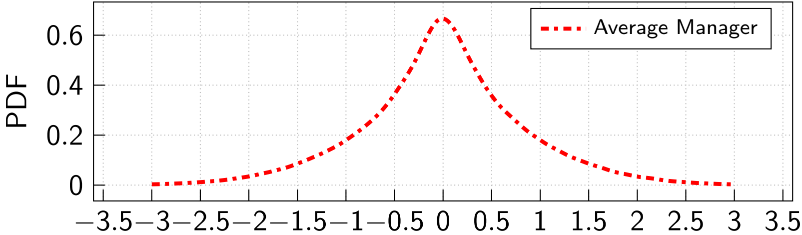
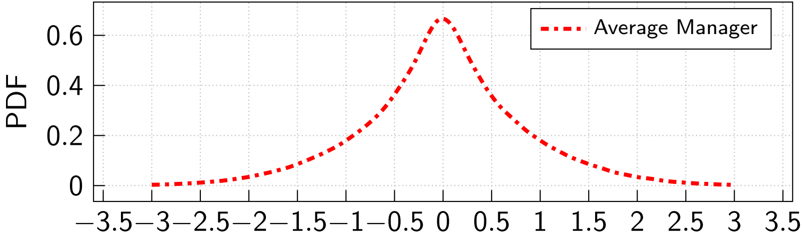
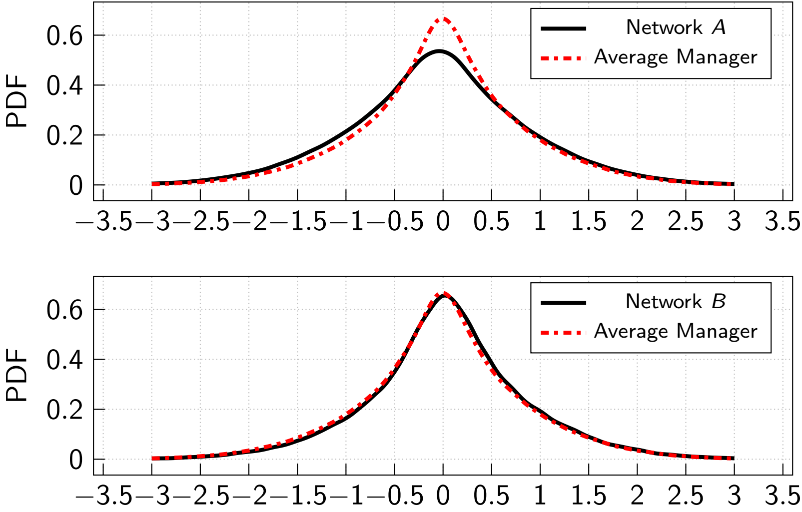
The average manager trades on luck

The Role of Luck





The Role of Luck



The Role of Luck

Consider the conditional $t-$statistic:

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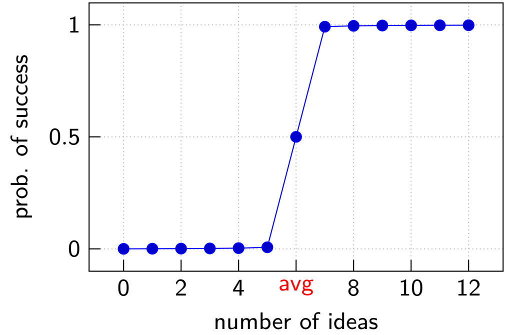

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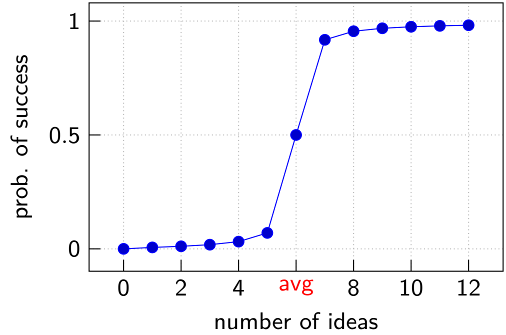
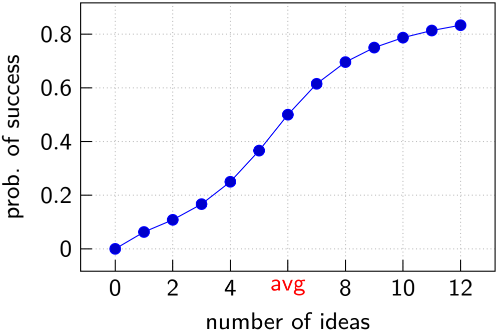


The Role of Luck

Consider the conditional $t-$statistic:

$$\mathbb{P}\left[\frac{\sigma_S^2|k_t|}{\sigma_S^2+o_t^c\phi_t}\text{sign}\left(\theta_t^i\right)\ \Delta_t>0\right]=\frac{1}{2}+\frac{1}{\pi}\tan^{-1}\left(\sqrt{\underbrace{\frac{\mathbb{E}[\Delta_t^2]}{\sigma_S^2k_t^2}}_{\frac{\text{Market-Timing Gains}}{\text{Information Speed}}}}\ \underbrace{\frac{n^i-\phi_t}{\sqrt{n_t^i}}}_{\text{Skill-to-Luck Ratio}}\right)$$



The Role of Luck

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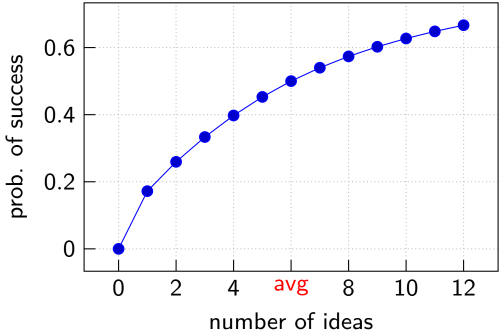
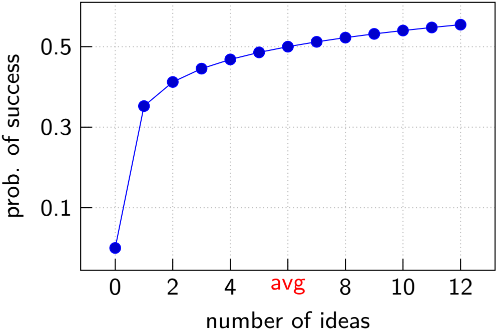
$$\mathbb{P}\left[\frac{\sigma_S^2|k_t|}{\sigma_S^2+o_t^c\phi_t}\text{sign}\left(\theta_t^i\right)\ \Delta_t>0\right]=\frac{1}{2}+\frac{1}{\pi}\tan^{-1}\left(\sqrt{\frac{\underbrace{\frac{\mathbb{E}[\Delta_t^2]}{\sigma_S^2k_t^2}}_{\text{Market-Timing Gains}}}{\text{Information Speed}}}\ \underbrace{\frac{n^i-\phi_t}{\sqrt{n_t^i}}}_{\text{Skill-to-Luck Ratio}}\right)$$



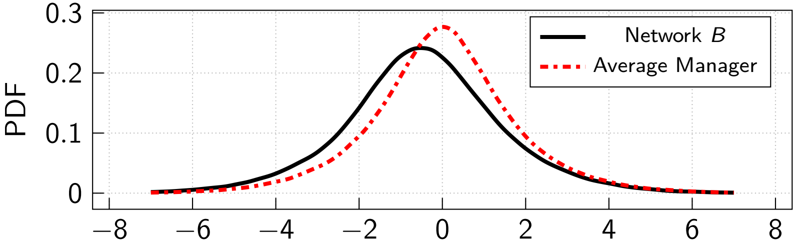
The Role of Luck

Consider the conditional $t-$statistic:

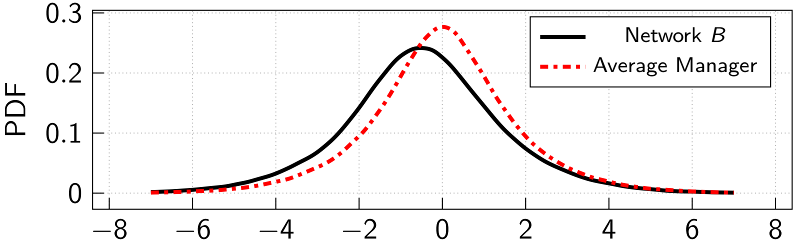
$$\mathbb{P}\left[\frac{\sigma_S^2|k_t|}{\sigma_S^2+o_t^c\phi_t}\text{sign}\left(\theta_t^i\right)\ \Delta_t>0\right]=\frac{1}{2}+\frac{1}{\pi}\tan^{-1}\left(\sqrt{\underbrace{\frac{\mathbb{E}[\Delta_t^2]}{\sigma_S^2k_t^2}}_{\frac{\text{Market-Timing Gains}}{\text{Information Speed}}}}\ \underbrace{\frac{n^i-\phi_t}{\sqrt{n_t^i}}}_{\substack{\text{Skill-to-Luck}\\\text{Ratio}}}\right)$$

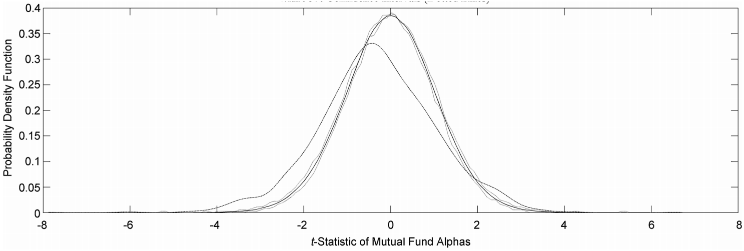


The Role of Luck



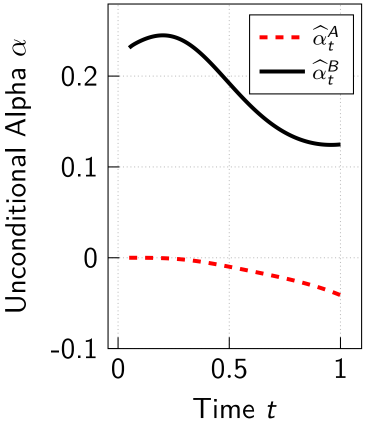
The Role of Luck





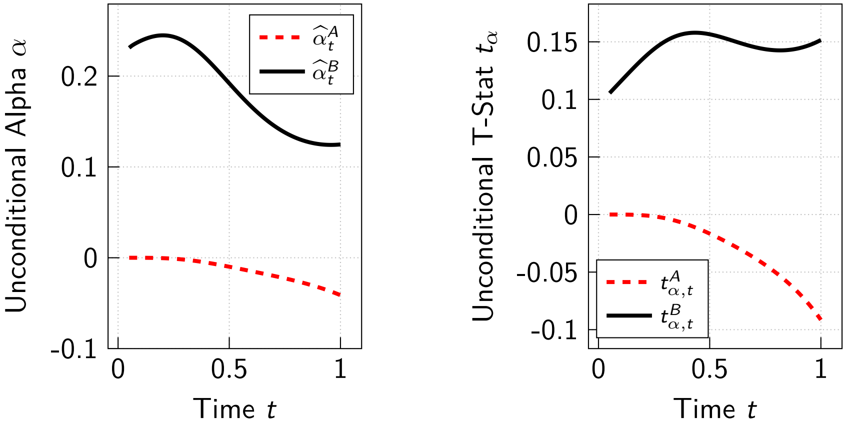
SOURCE: KOSOWSKI, TIMMERMANN, WERMERS & WHITE (JF, 2006)

Persistence



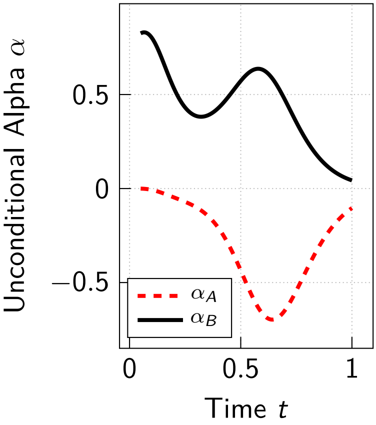
Benchmark Calibration

Persistence



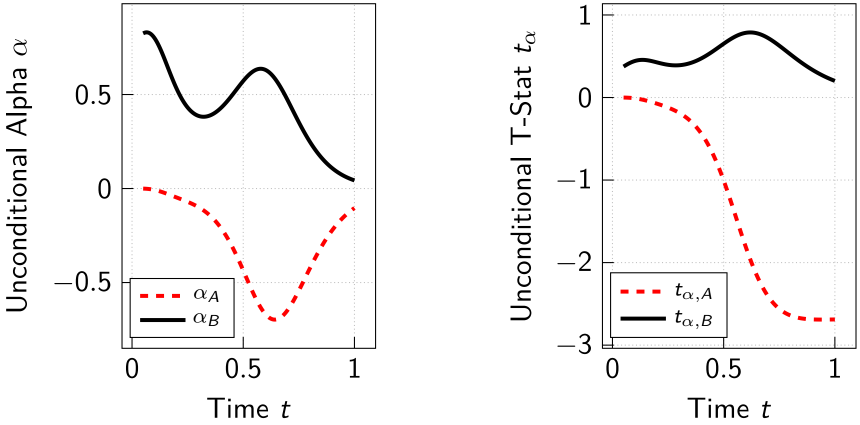
Benchmark Calibration

Persistence



High-Intensity Calibration

Persistence



High-Intensity Calibration

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