The Social Dynamics of Performance

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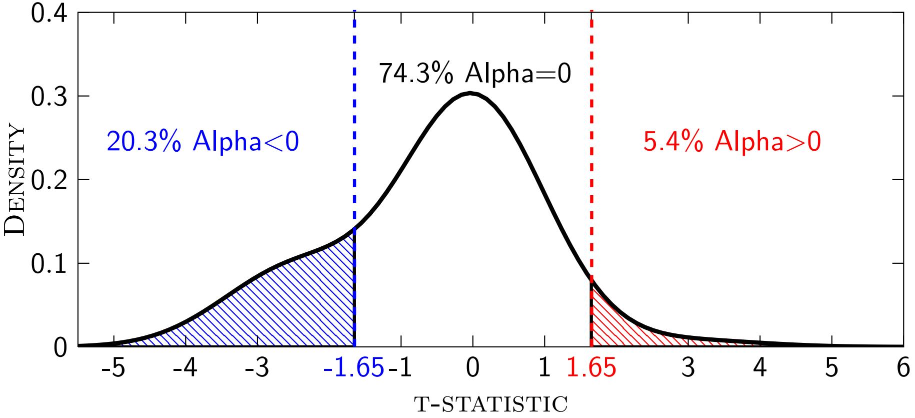
ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

WFA, 2013

A pervasive fact in the mutual fund industry

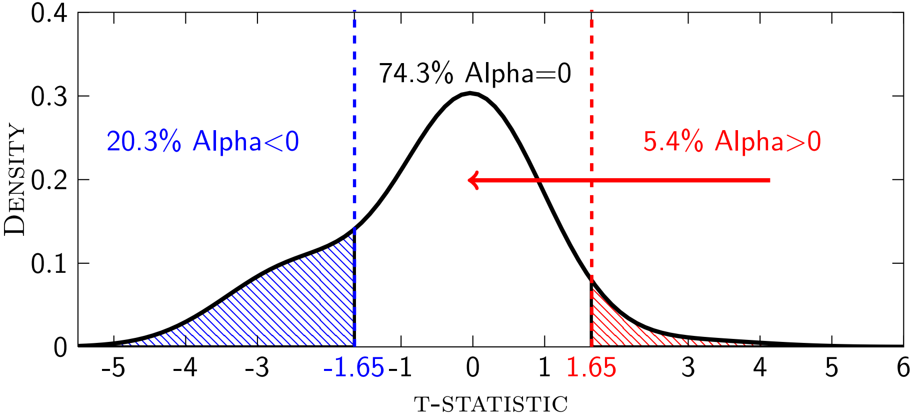


Cross-sectional distribution of alpha's t-stats

Skilled managers merely represent 2% of the population

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

A pervasive fact in the mutual fund industry

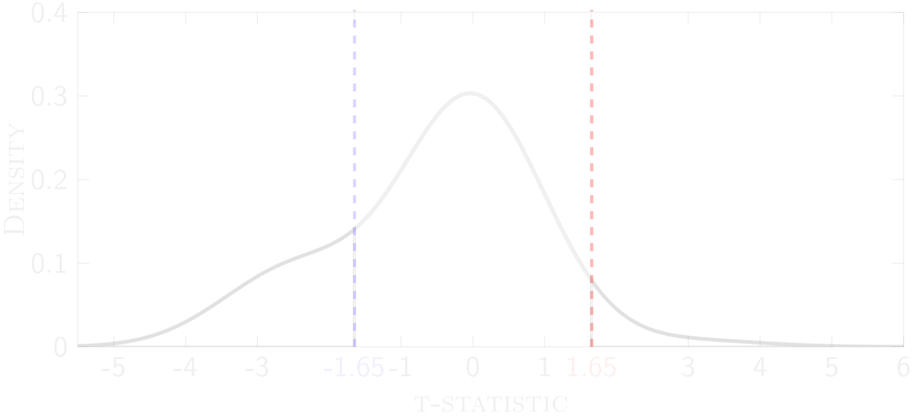


Cross-sectional distribution of alpha's t-stats

Managers do not maintain their performance

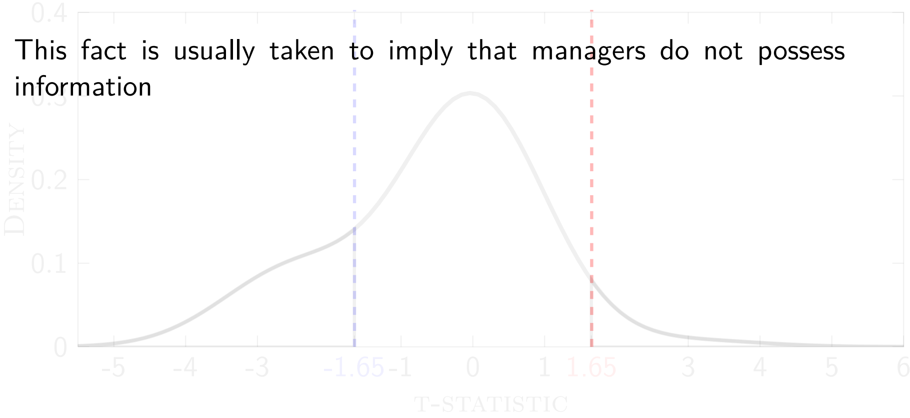
Source: Barras, Scaillet & Wermers (JF, 2010)

Puzzling Evidence



Puzzling Evidence

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



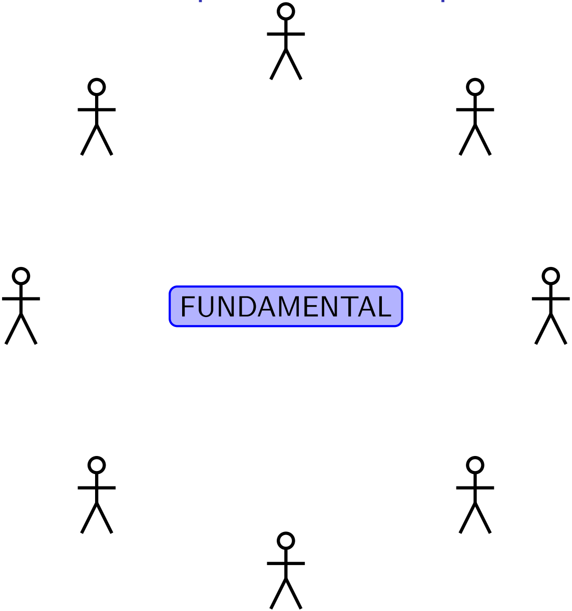
Puzzling Evidence

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

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

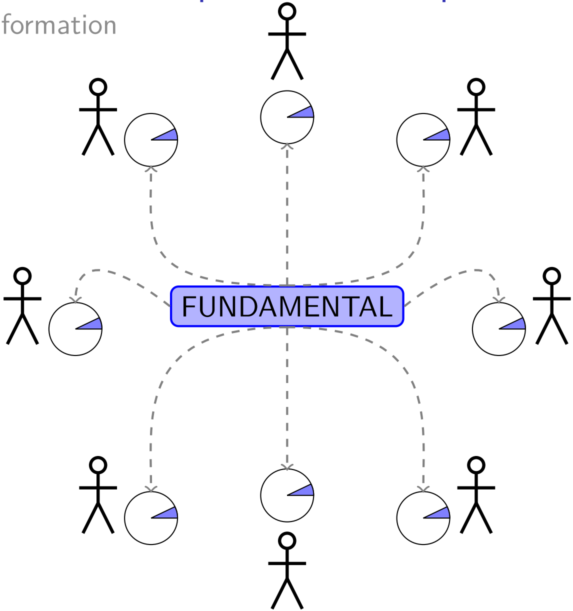
- Chevalier and Ellison (1999): SAT effect
- Coval and Moskowitz (2001): Local Informational Advantage
- Cohen, Frazzini, and Malloy (2008): Educational Networks
- Christoffersen and Sarkissian (2009): Knowledge Spillovers

A Standard Rational-Expectations Setup



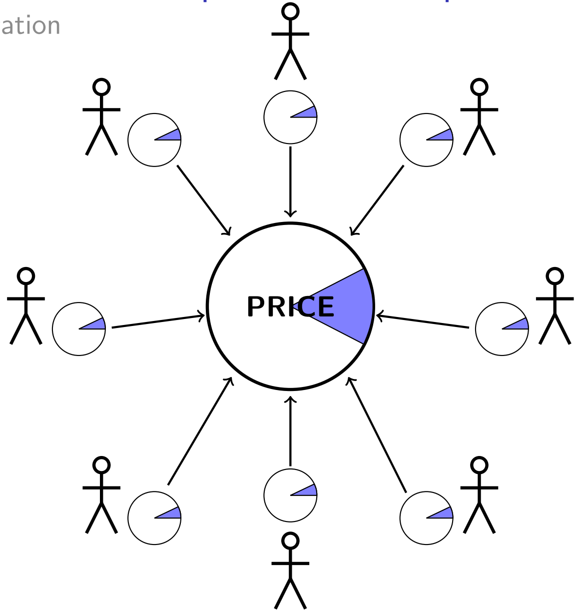
A Standard Rational-Expectations Setup

Dispersed Information



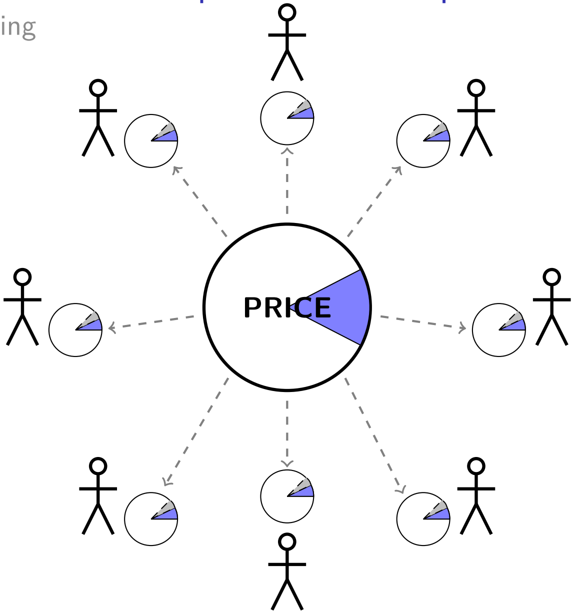
A Standard Rational-Expectations Setup

Aggregation



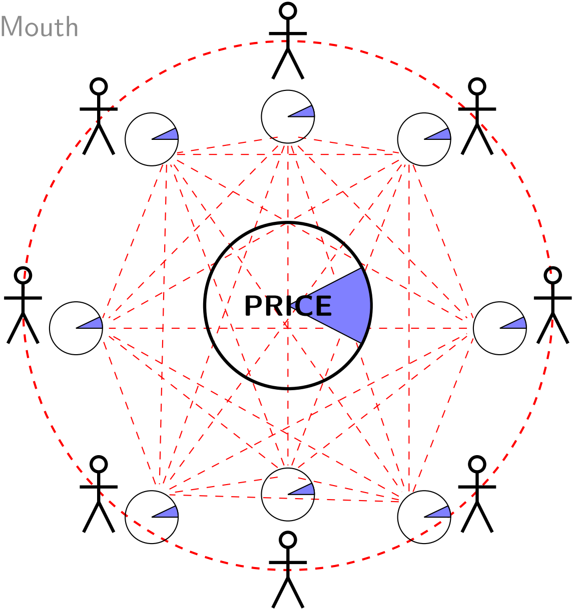
A Standard Rational-Expectations Setup

Learning



My Contribution

Word-of-Mouth



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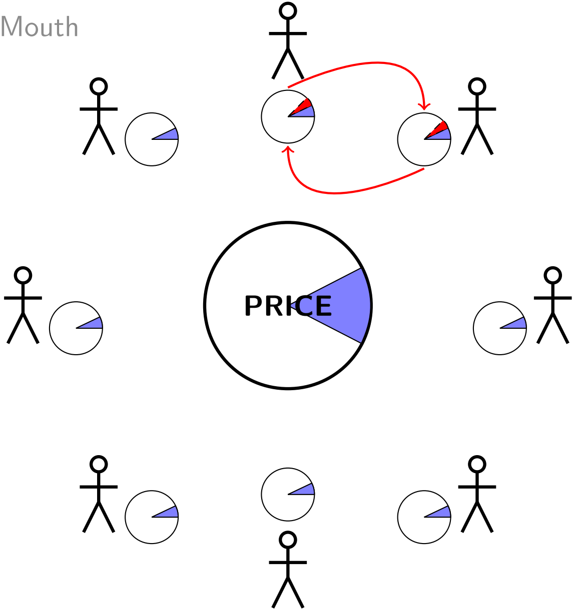

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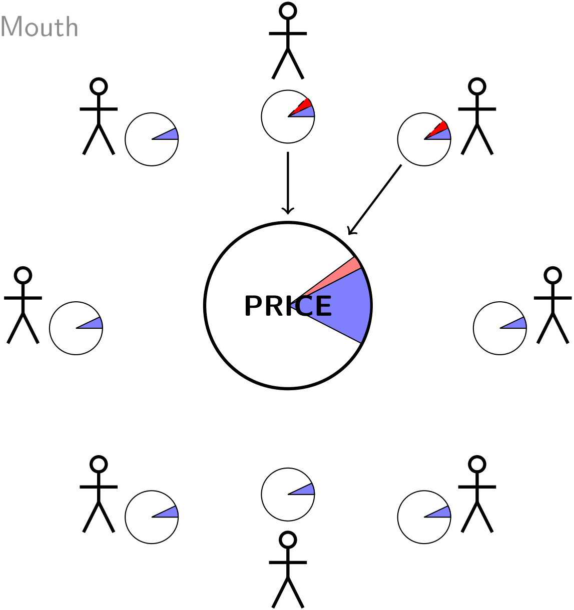

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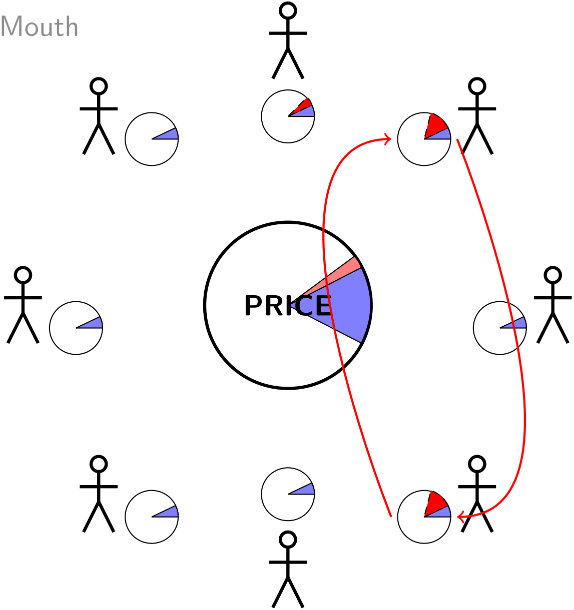

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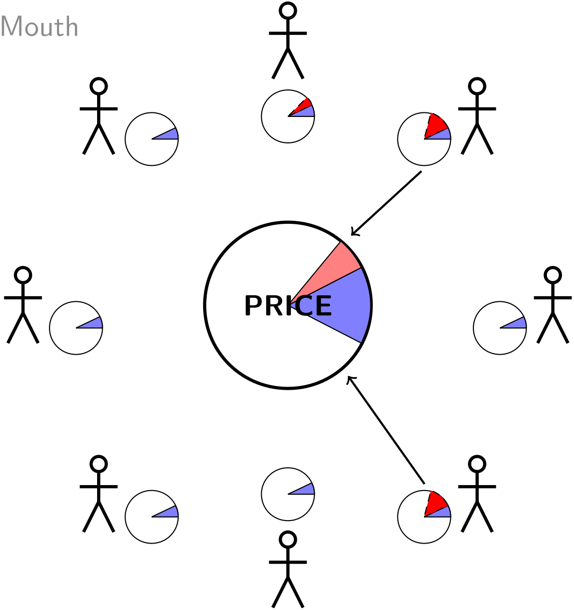

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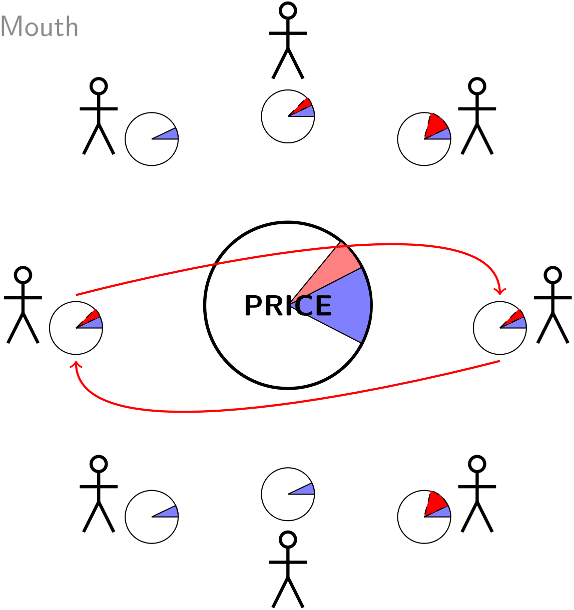

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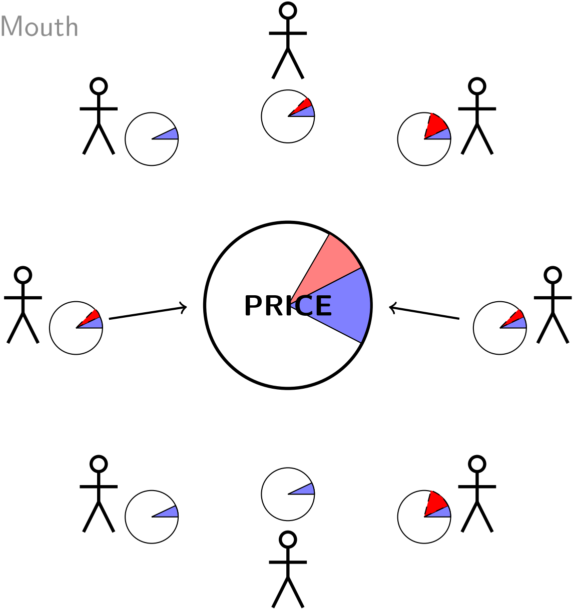

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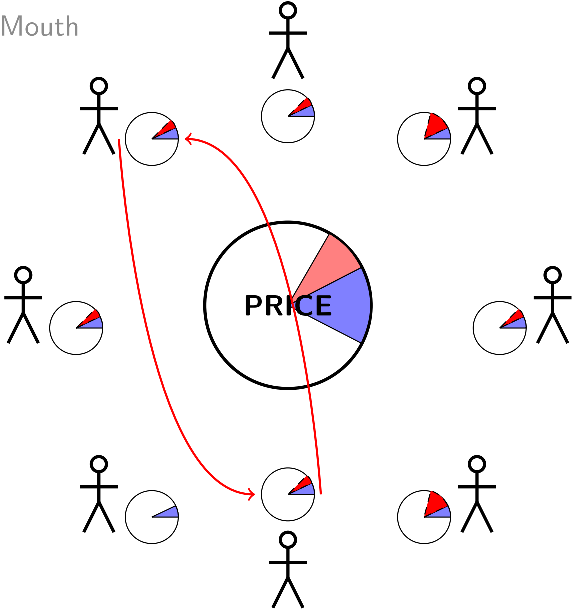

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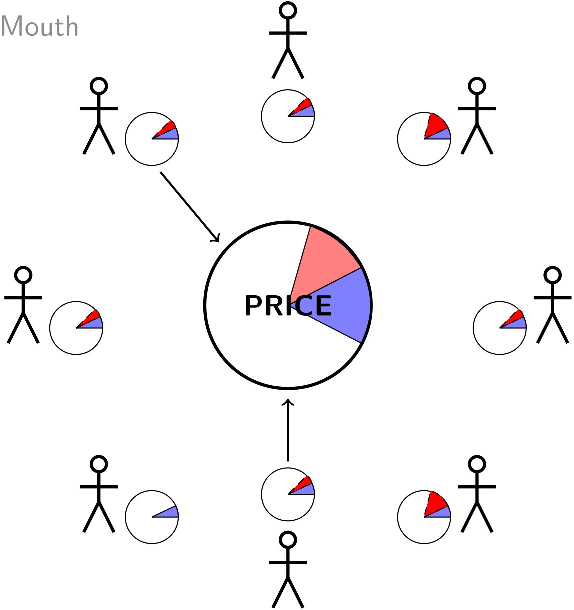

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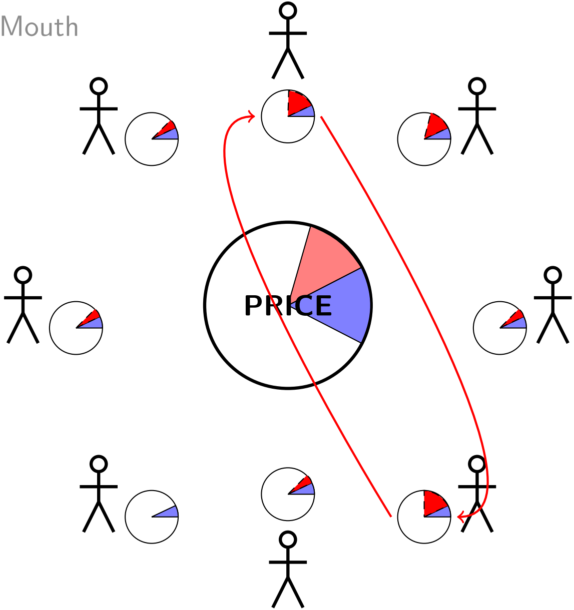

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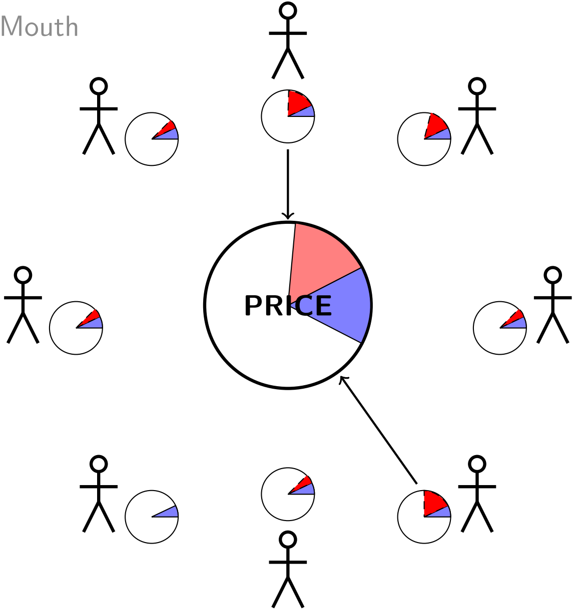

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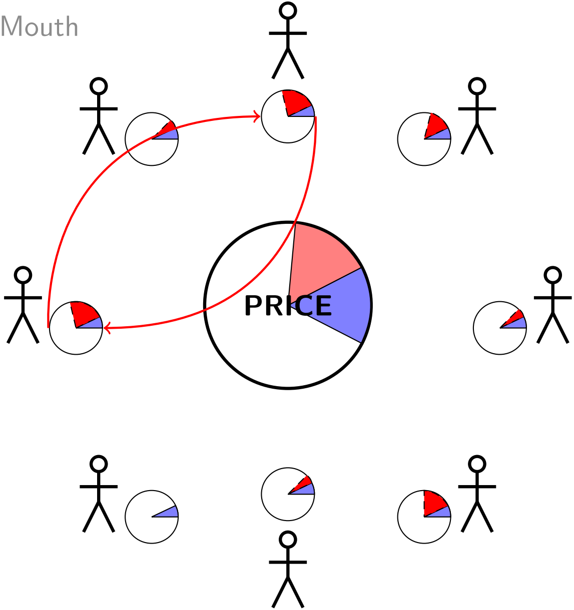

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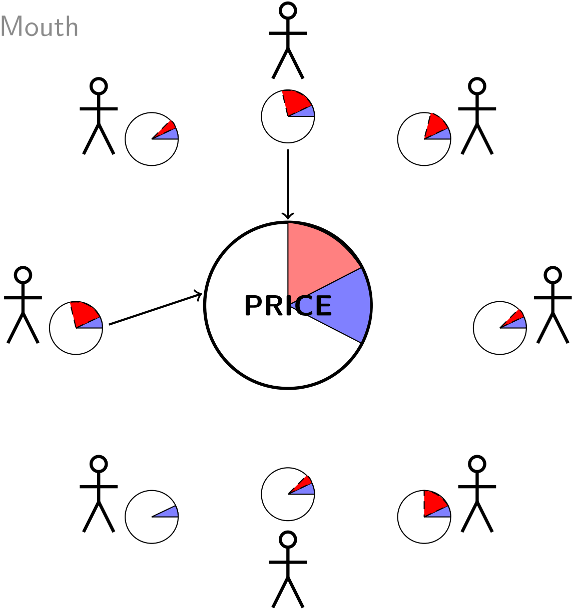

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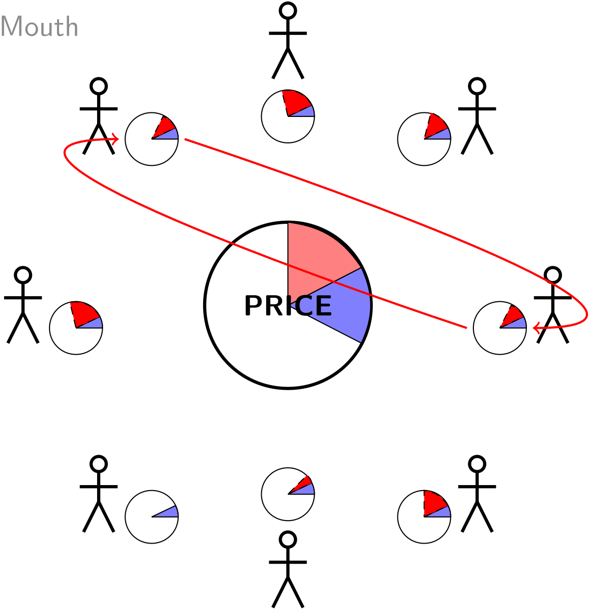

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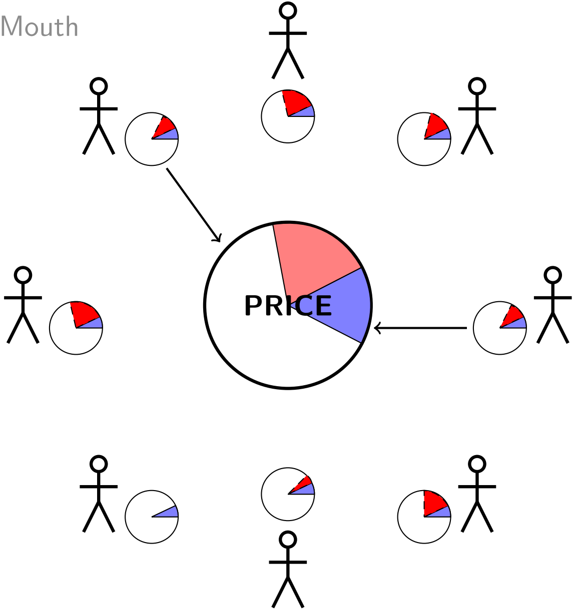

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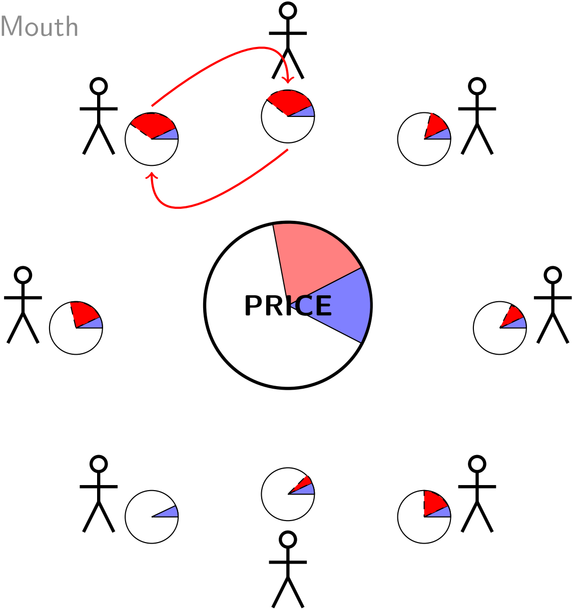

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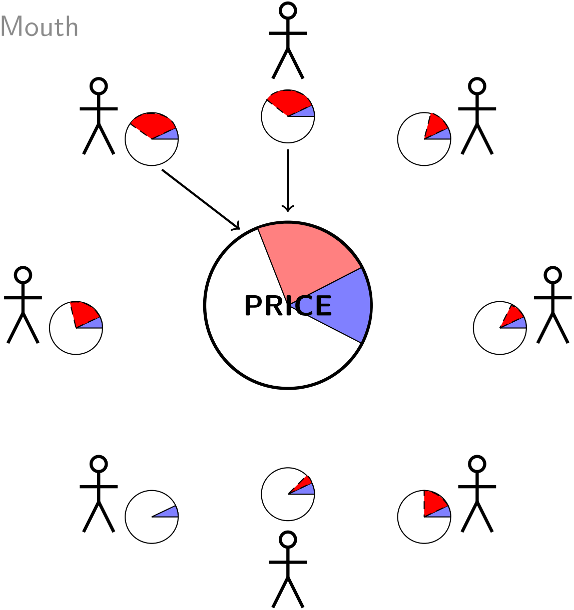
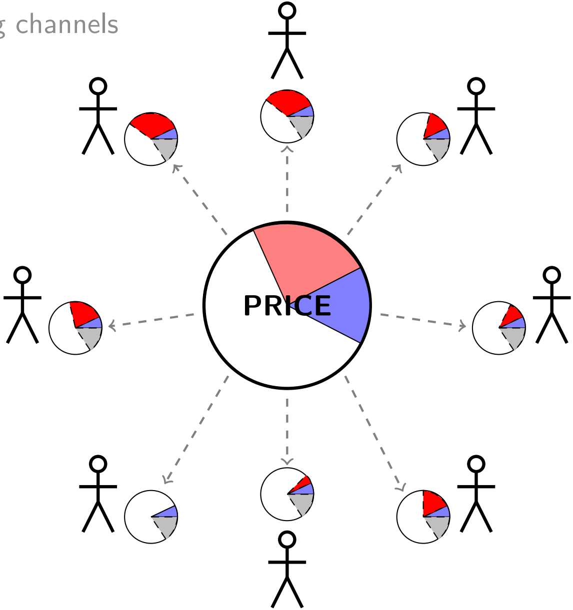


My Contribution

Two learning channels



Outline

I Model

II Solution Method

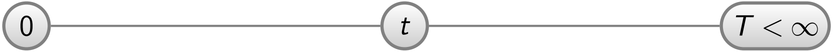
III Results

Outline

Setup

Setup

Continuous trading on $[0, T)$



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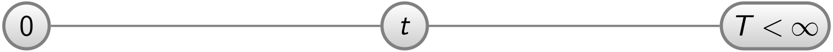

Announcement

$\Pi + \delta$

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

$\delta \sim \mathcal{N}(0, \sigma_{\delta}^2)$
(cannot learn)

Setup

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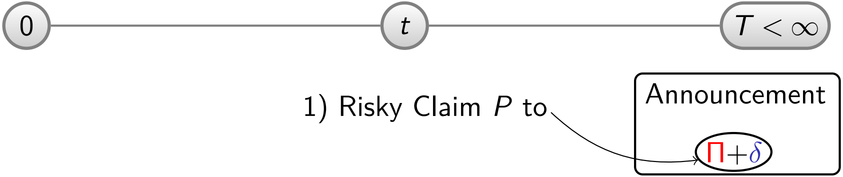

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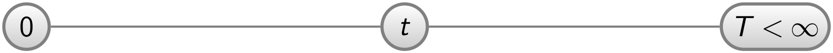

1) Risky Claim P to

Announcement

$\Pi + \delta$

2) Bond $(r = 0)$

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

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Setup

Continuous trading on $[0, T)$

0 — t — $T < \infty$

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

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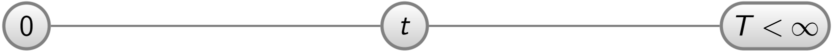

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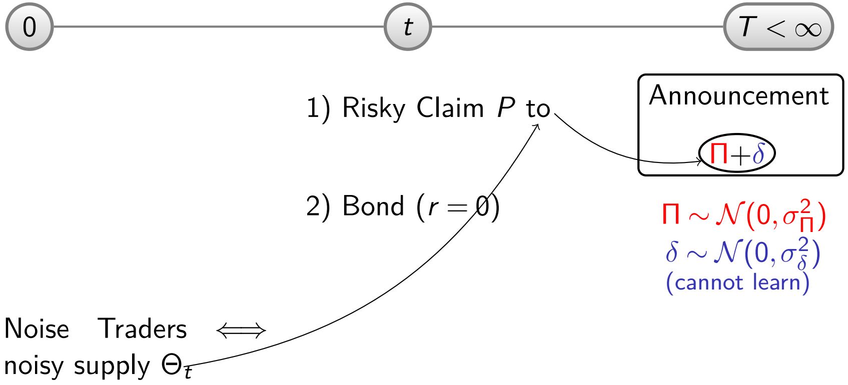
No fund flows: managers maximize $E[U[W_T^j]|\mathcal{F}_t^j], \quad j \in \{I, i\}$

Setup

Continuous trading on $[0, T)$



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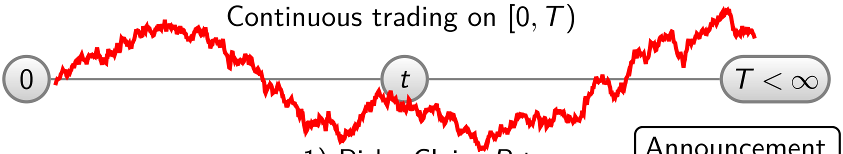

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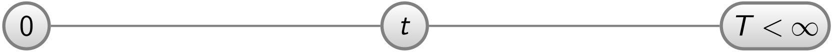
Noise Traders $\iff$ noisy supply Θ_t

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

Introducing Social Dynamics



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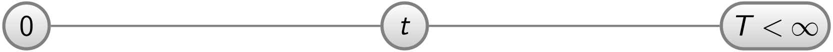
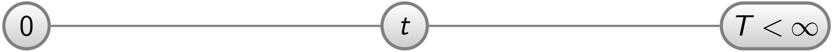


Each manager l starts with an idea $S_1^l = \Pi + \epsilon_1^l$

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

Introducing Social Dynamics



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Managers meet at Poisson random times.
Ideas percolate with intensity η.

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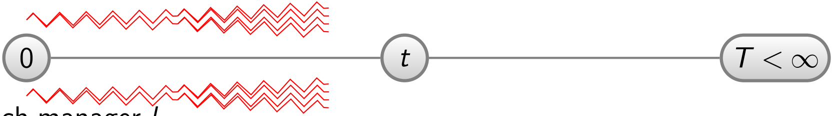

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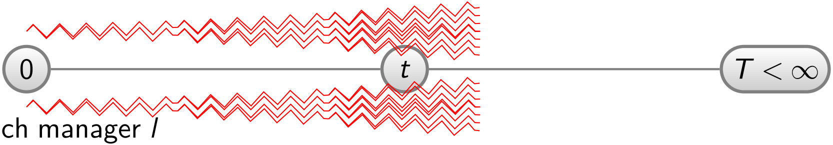
$$\{S_j^l\}_{j=1}^3 = \{S_1^l,\ S_2^l,\ S_3^l\}$$

Introducing Social Dynamics



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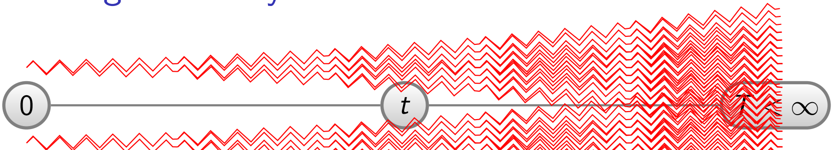
$$\{S_j^l\}_{j=1}^6 = \{S_1^l,\ S_2^l,\ S_3^l,\ S_4^l,\ S_5^l,\ S_6^l\}$$

Introducing Social Dynamics

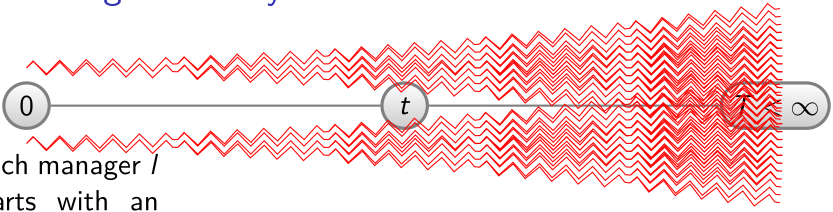


Each manager l starts with an idea $S_1^l = \Pi + \epsilon_1^l$

Managers meet at Poisson random times.
Ideas percolate with intensity η.

$$\{S_j^l\}_{j=1}^{n_t} = \{S_1^l, \, S_2^l, \ldots, \, S_{n_t}^l\}$$

Introducing Social Dynamics



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Managers meet at Poisson random times.
Ideas percolate with intensity η.

$$\{S_j^l\}_{j=1}^{n_t} \iff \bar{S}_{n_t}^l \equiv \Pi + \frac{1}{n_t} \sum_{j=1}^{n_t} \epsilon_j^l$$

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 $n \geq K$

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

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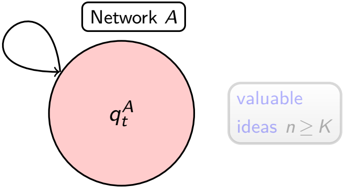

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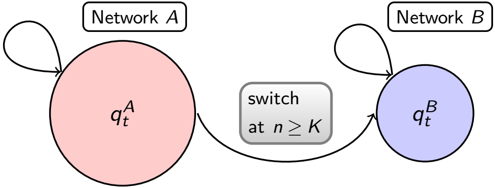

\# of ideas n: $[1, \dots, K-1]$ $[K, \dots \quad)$

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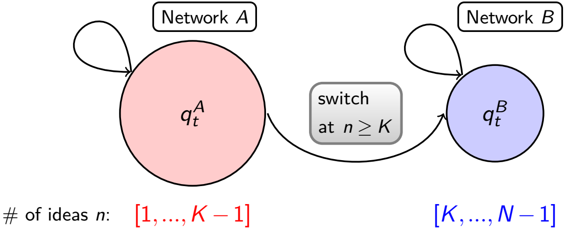

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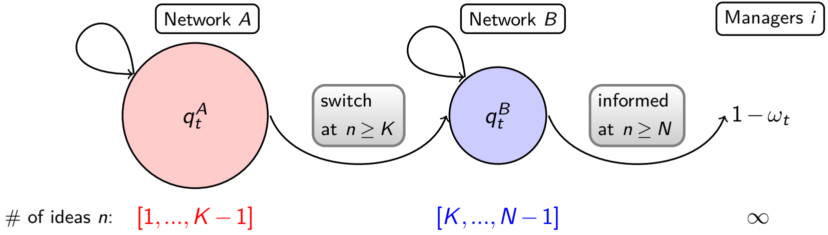

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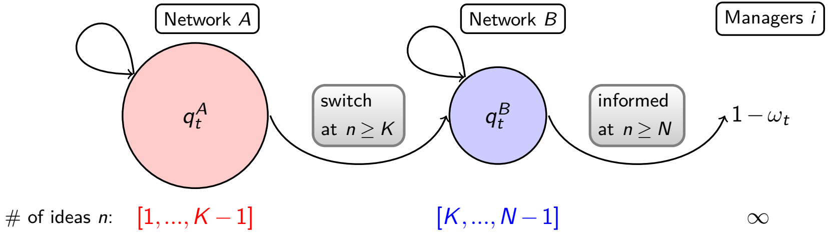

Main Purpose: allow managers to longer preserve their informational advantage by clustering their information

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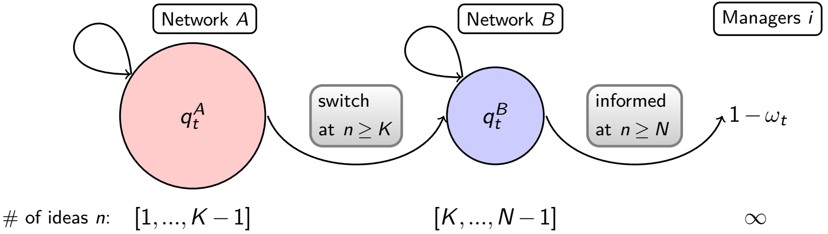
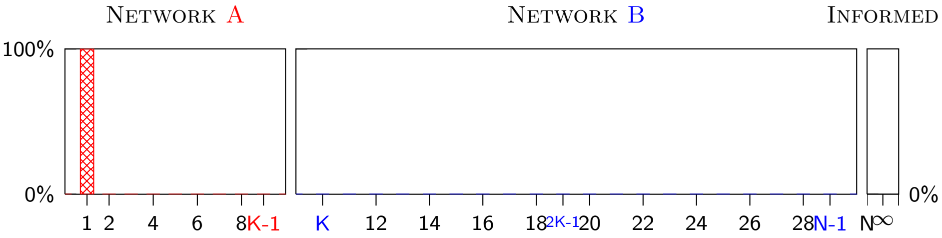


Cross-Sectional Distribution at time $t=0$



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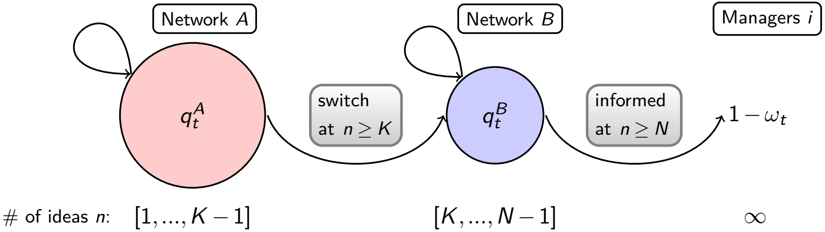
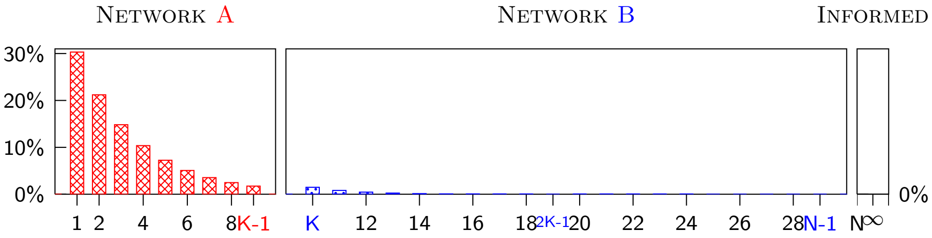


Cross-Sectional Distribution at time $t = 0.2$



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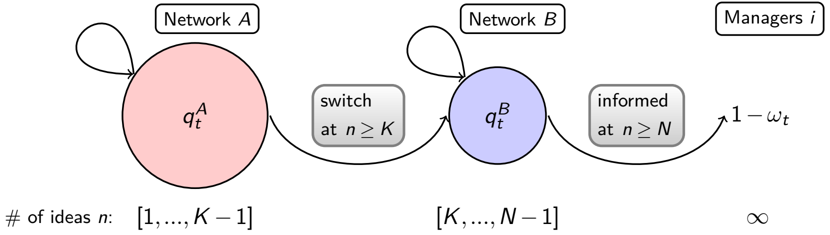
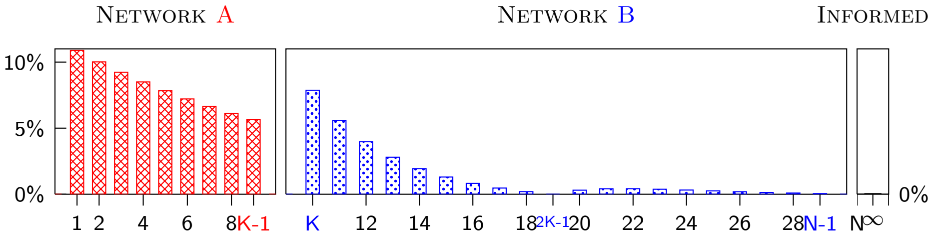


Cross-Sectional Distribution at time $t = 0.4$



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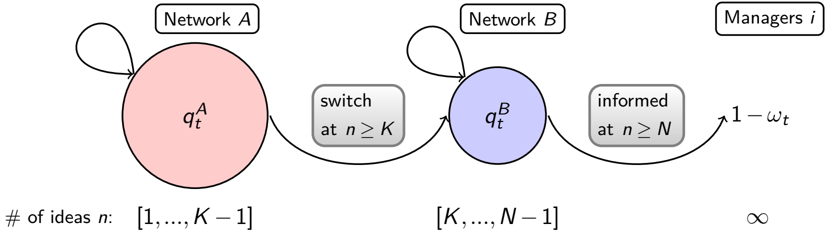
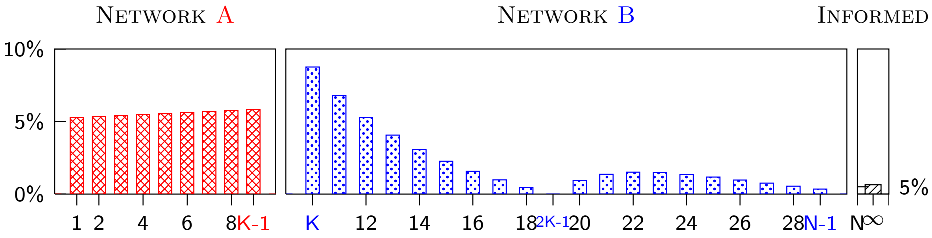


Cross-Sectional Distribution at time $t = 0.6$



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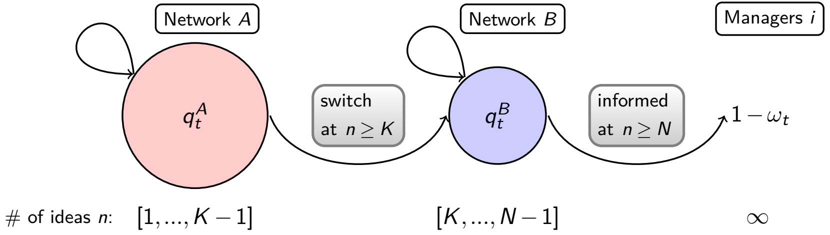
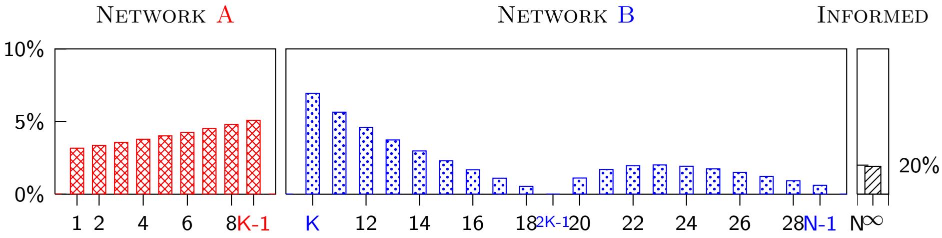
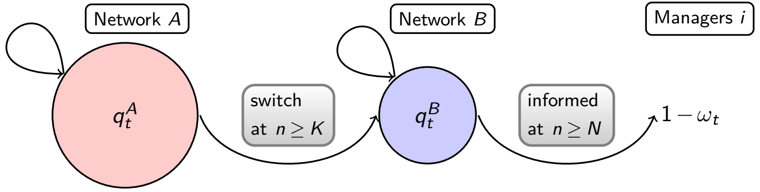


Cross-Sectional Distribution at time $t = 0.8$

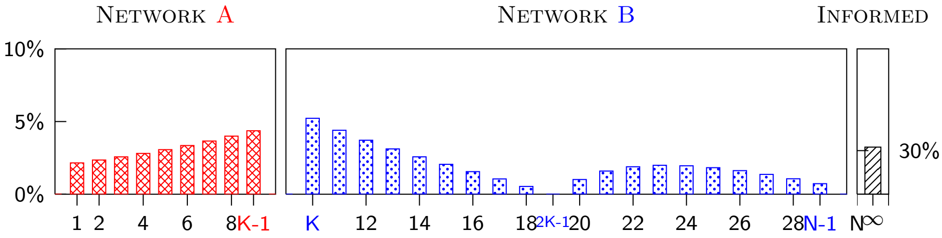


Introducing Social Dynamics



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

Cross-Sectional Distribution at time $t = 1$



Outline

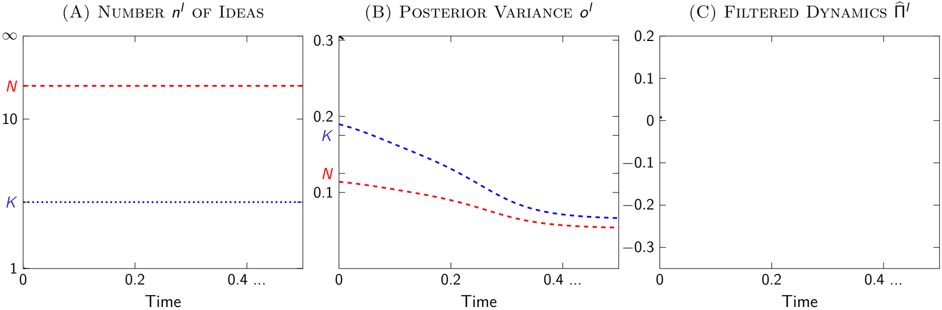
Word-of-Mouth Learning

Illustration of the learning process

$$\mathrm{d}\widehat{\Pi}_t^l = o_{t\_}^l\, k_t \mathrm{d}\widehat{B}_t^l + Z_t^l \mathrm{d}N_t^l,$$

$$\mathrm{d}o_t^l = -k_t^2 (o_{t\_}^l)^2 \mathrm{d}t - \frac{1}{\sigma_S^2} o_{t\_}^l\, o_t^l m_t \mathrm{d}N_t^l,$$

$$\mathrm{d}n_t^l = \left(m_t \mathbf{1}_{\{m_t + n_{t\_}^l \in \mathbb{A} \cup \mathbb{B}\}} + \infty \mathbf{1}_{\{m_t + n_{t\_}^l \notin \mathbb{A} \cup \mathbb{B}\}} \right) \mathrm{d}N_t^l, \qquad n_0^l = 1$$



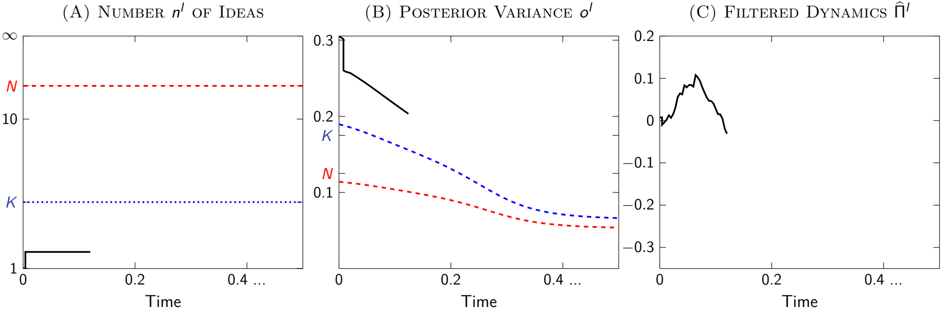
Word-of-Mouth Learning

Illustration of the learning process

$$d\widehat{\Pi}^l_t = o^l_{t\_}\, k_t d\widehat{B}^l_t + Z^l_t dN^l_t,$$

$$do^l_t = -k^2_t (o^l_{t\_})^2 dt - \frac{1}{\sigma^2_S} o^l_{t\_}\, o^l_t m_t dN^l_t,$$

$$dn^l_t = \left(m_t \mathbf{1}_{\{m_t + n^l_{t\_} \in \mathbb{A}\cup\mathbb{B}\}} + \infty \mathbf{1}_{\{m_t + n^l_{t\_} \notin \mathbb{A}\cup\mathbb{B}\}} \right) dN^l_t, \qquad n^l_0 = 1$$



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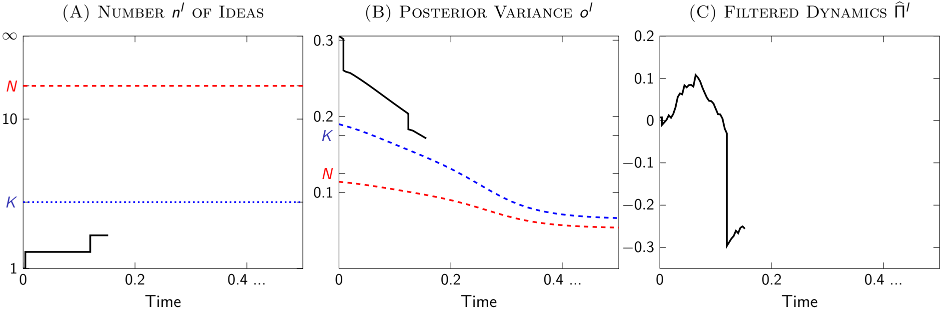

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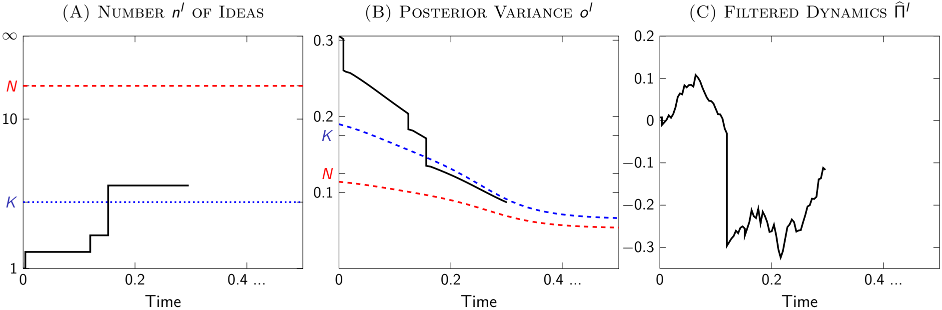

Word-of-Mouth Learning

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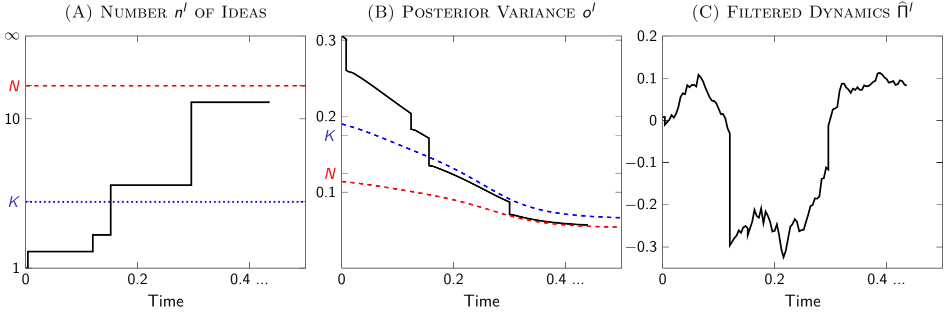


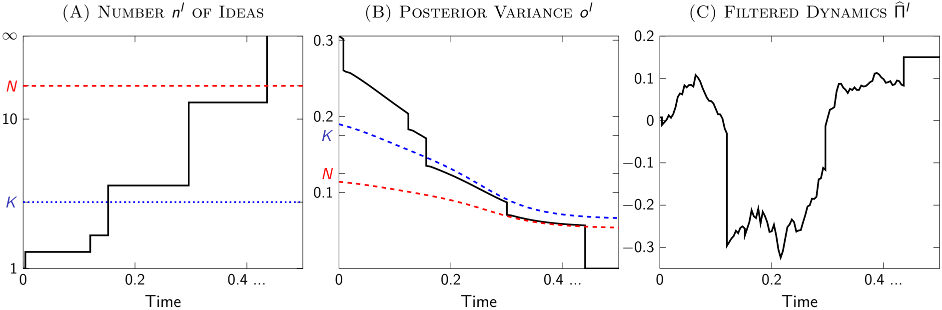
Word-of-Mouth Learning

Illustration of the learning process

$$d\widehat{\Pi}_t^I = o_{t\_}^I \, k_t d\widehat{B}_t^I + Z_t^I dN_t^I,$$

$$do_t^I = -k_t^2 (o_{t\_}^I)^2 dt - \frac{1}{\sigma_S^2} o_{t\_}^I o_t^I m_t dN_t^I,$$

$$dn_t^I = \left(m_t \mathbf{1}_{\{m_t + n_{t\_}^I \in \mathbb{A} \cup \mathbb{B}\}} + \infty \mathbf{1}_{\{m_t + n_{t\_}^I \notin \mathbb{A} \cup \mathbb{B}\}} \right) dN_t^I, \qquad n_0^I = 1$$



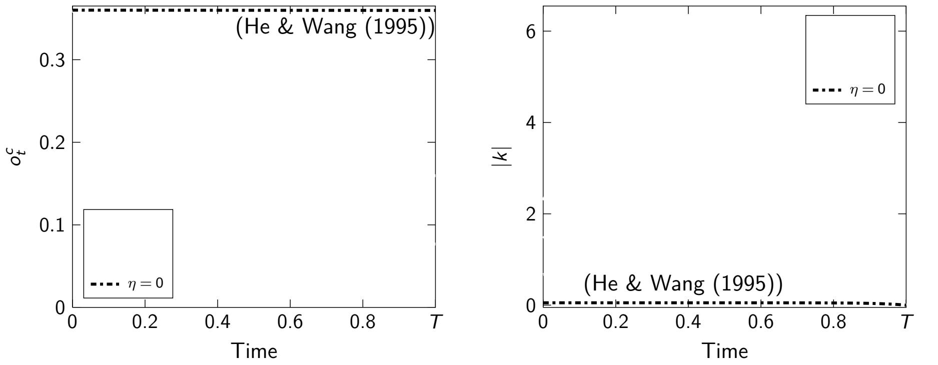
Price Informativeness

The speed of information revelation through prices:

$$k_t = \frac{1}{\sigma_\Theta}\left(\frac{\mathrm{d}}{\mathrm{d}t}\frac{\lambda_{1,t}}{\lambda_{2,t}} + a_\Theta \frac{\lambda_{1,t}}{\lambda_{2,t}}\right)$$

drives common uncertainty $\mathrm{d}o_t^c = -k_t^2 (o_t^c)^2 \mathrm{d}t$.

(A) Common Uncertainty regarding Π (B) Price-Revelation Speed $|k|$



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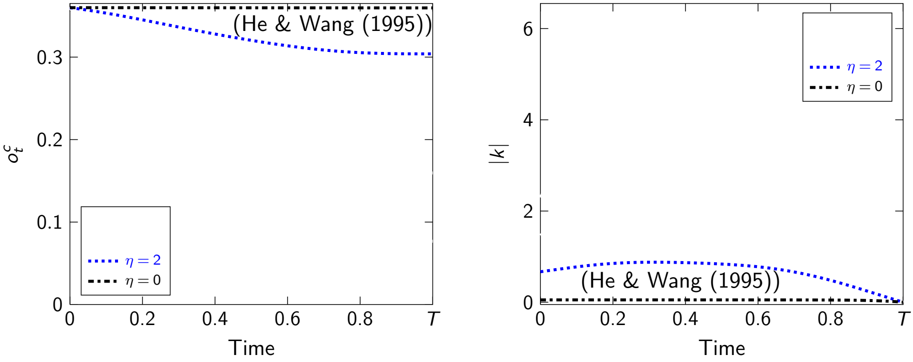

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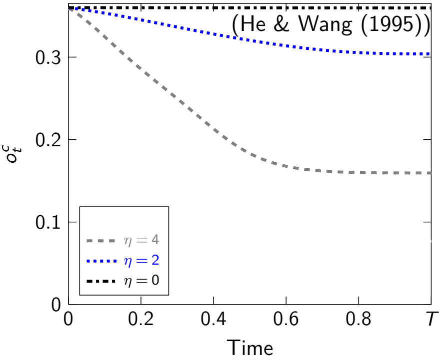
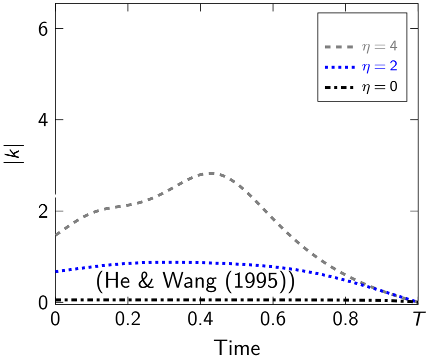


(B) Price-Revelation Speed $|k|$



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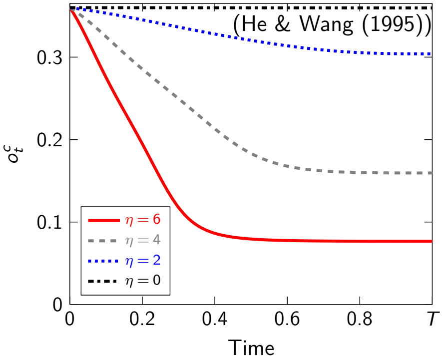
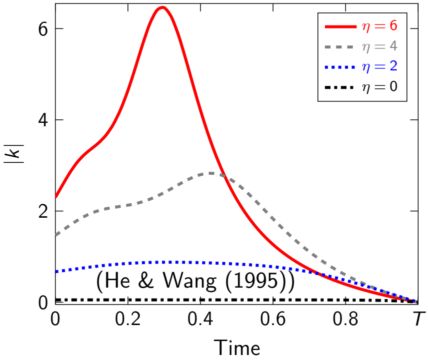
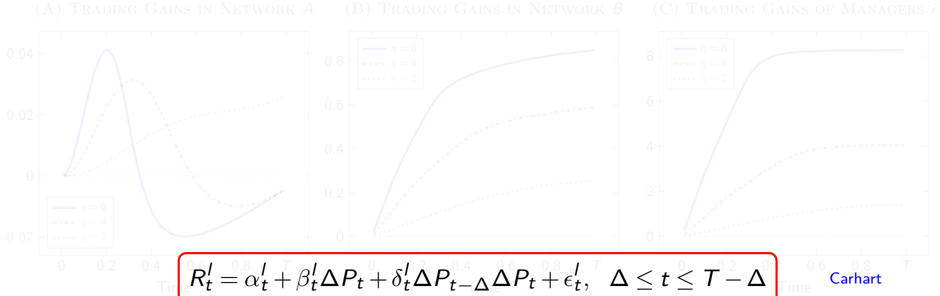


(B) Price-Revelation Speed $|k|$



Outline

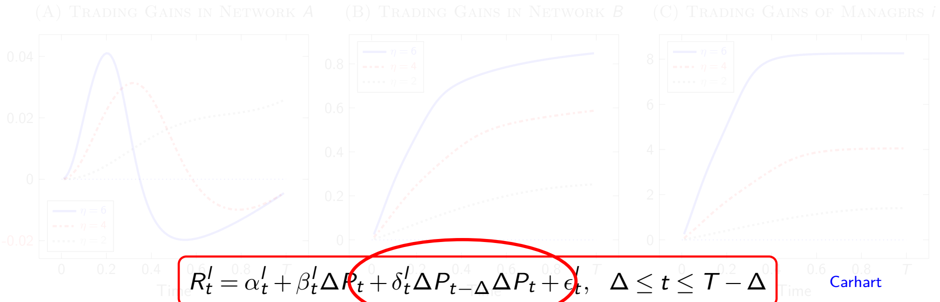
Performance (Alpha)



$$R_t^I = \alpha_t^I + \beta_t^I \Delta P_t + \delta_t^I \Delta P_{t-\Delta} \Delta P_t + \epsilon_t^I, \quad \Delta \leq t \leq T - \Delta$$

Carhart

Performance (Alpha)



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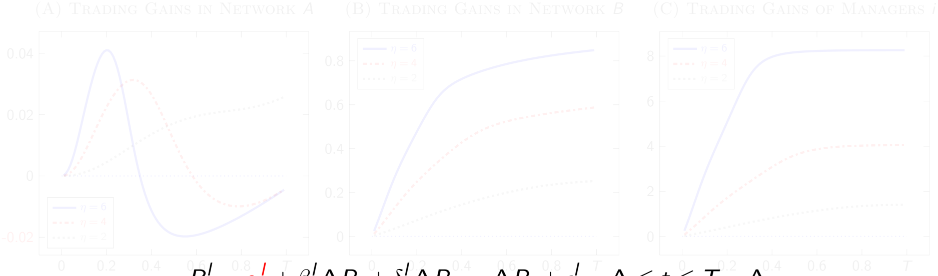
Carhart

Time-Series Momentum Factor

Moskowitz, Oii & Pedersen (2011)

Performance (Alpha)



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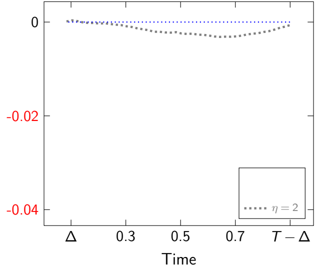
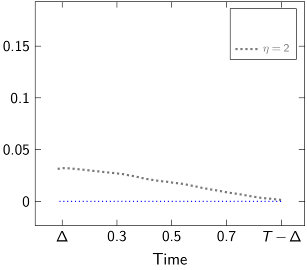
Performance (Alpha)

$$R_t^l = \alpha_t^l + \beta_t^l \Delta P_t + \delta_t^l \Delta P_{t-\Delta} \Delta P_t + \epsilon_t^l, \quad \Delta \le t \le T - \Delta$$

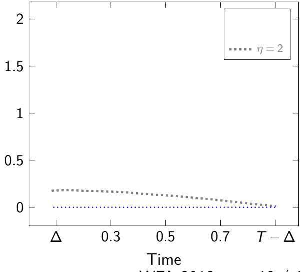
(A) Alpha in Network A



(B) Alpha in Network B



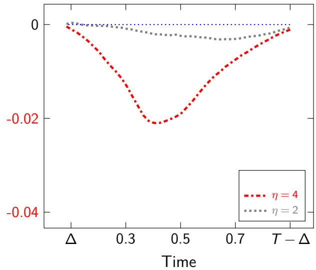
(C) Alpha of Managers i



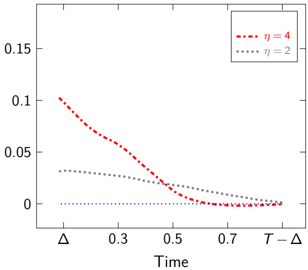
Performance (Alpha)

$$R_t^I = \alpha_t^I + \beta_t^I \Delta P_t + \delta_t^I \Delta P_{t-\Delta} \Delta P_t + \epsilon_t^I, \quad \Delta \leq t \leq T - \Delta$$

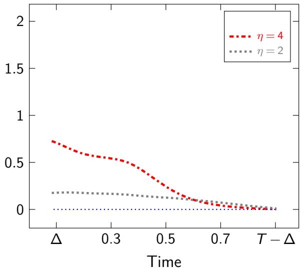
(A) Alpha in Network *A*



(B) Alpha in Network *B*

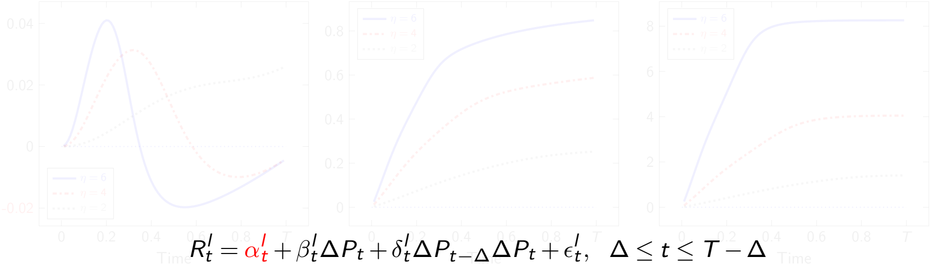


(C) Alpha of Managers *i*



Performance (Alpha)

(A) Trading Gains in Network A (B) Trading Gains in Network B (C) Trading Gains of Managers i



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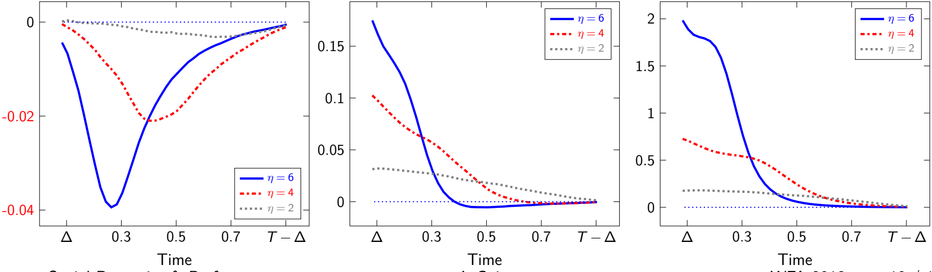
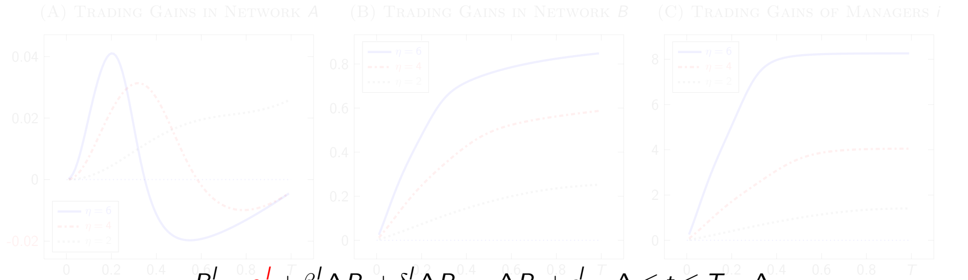
(A) Alpha in Network A (B) Alpha in Network B (C) Alpha of Managers i



Performance (Alpha)



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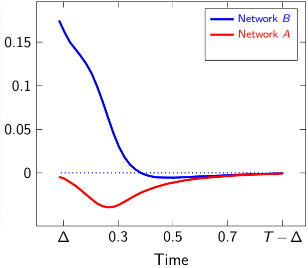
(B) Alpha in Network B



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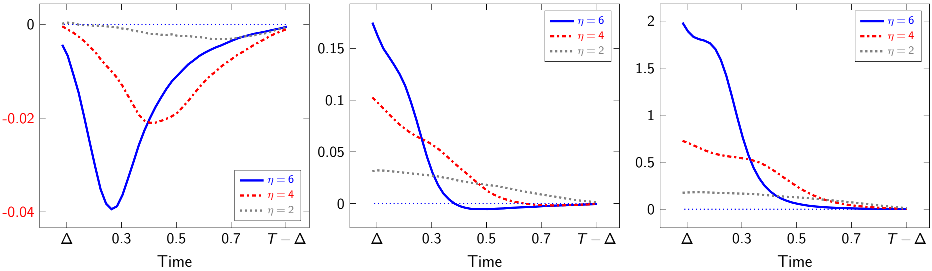
(A) Alpha in Network A (B) Alpha in Network B (C) Alpha of Managers i



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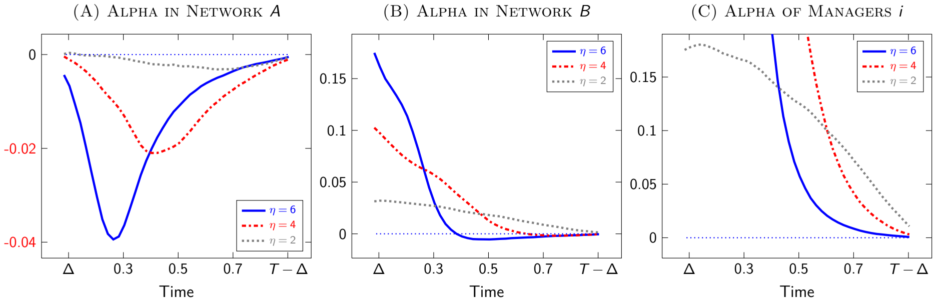
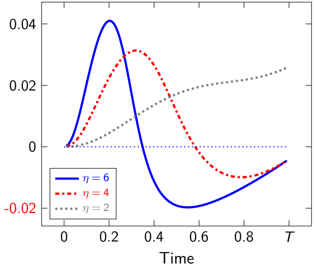
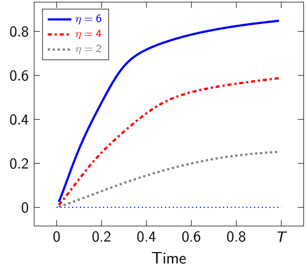


Performance (Dollar Value vs. Alpha)

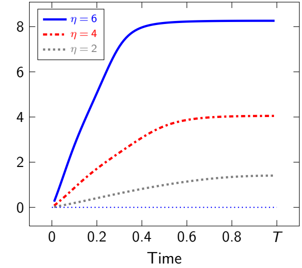
(A) Trading Gains in Network A



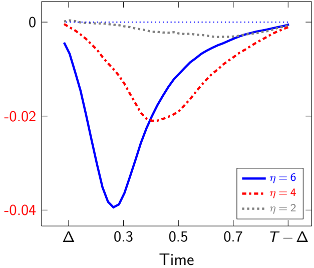
(B) Trading Gains in Network B



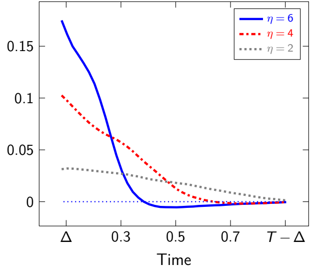
(C) Trading Gains of Managers i



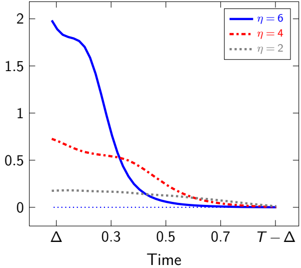
(A) Alpha in Network A



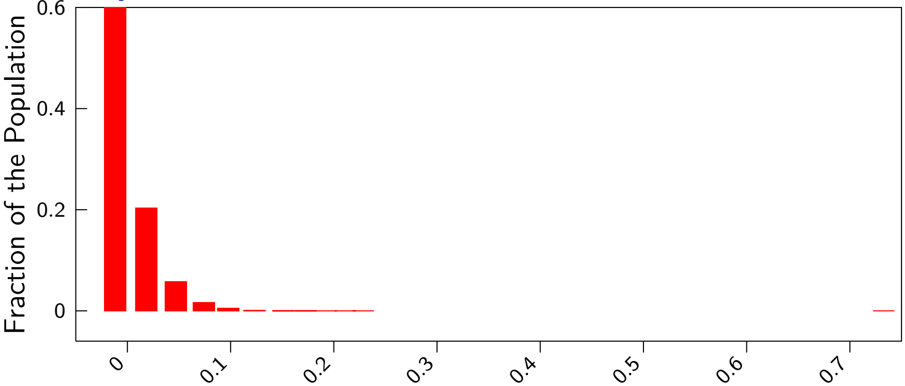
(B) Alpha in Network B



(C) Alpha of Managers i



Social Dynamics of Performance



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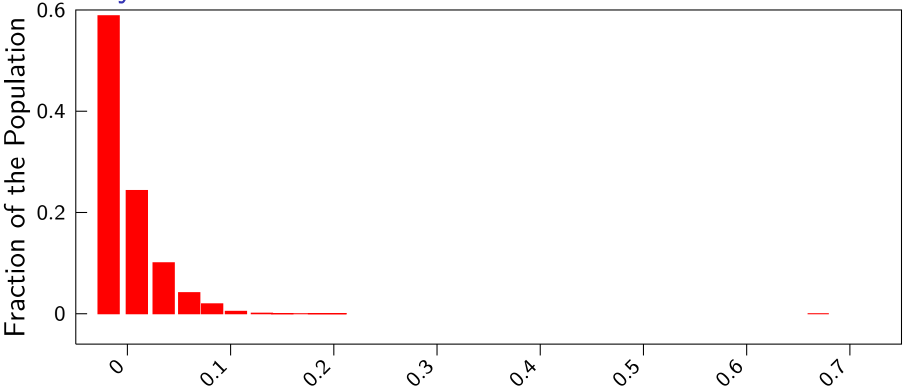

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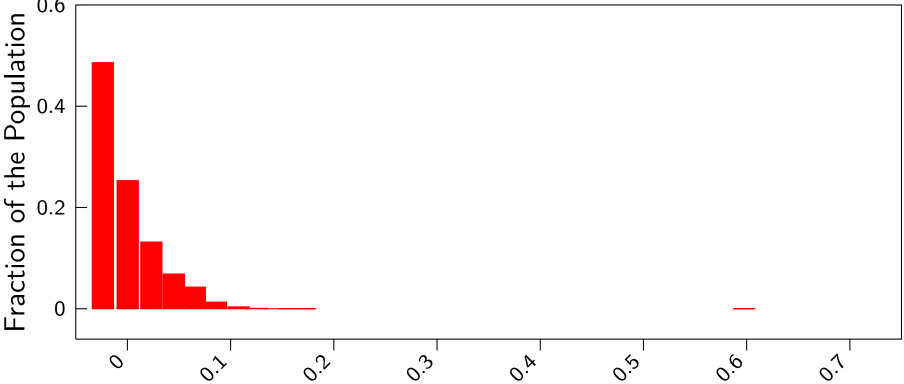

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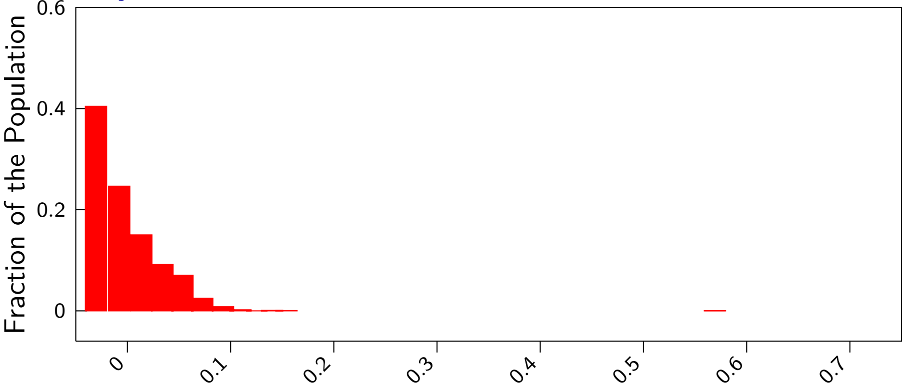

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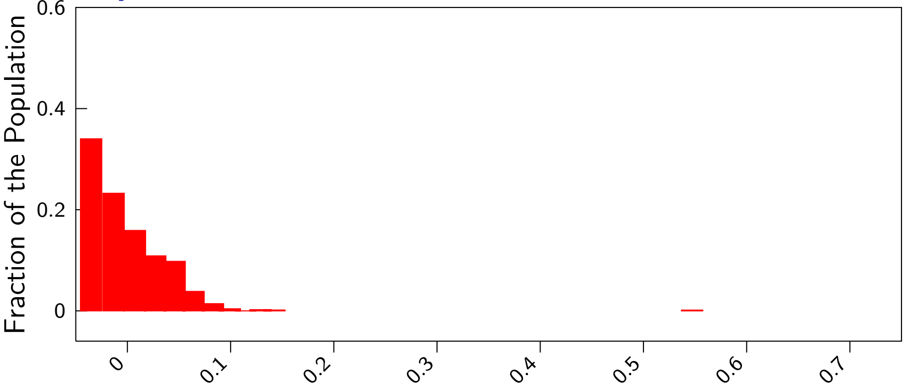

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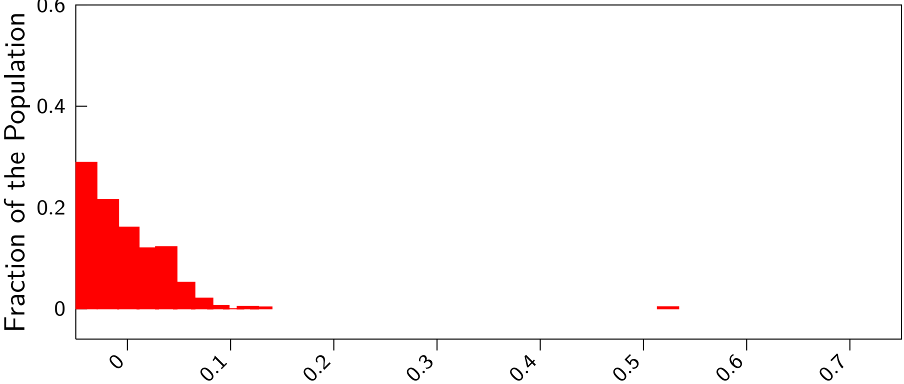

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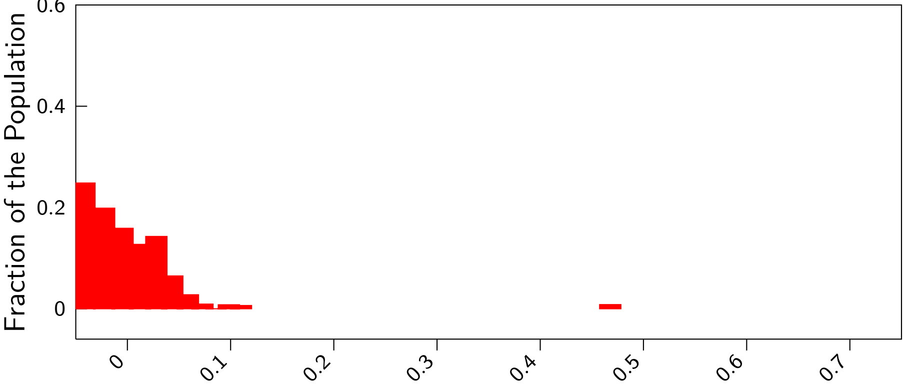

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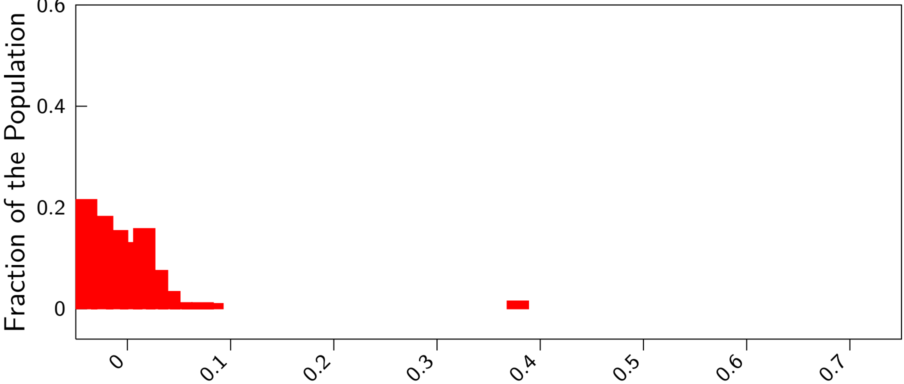

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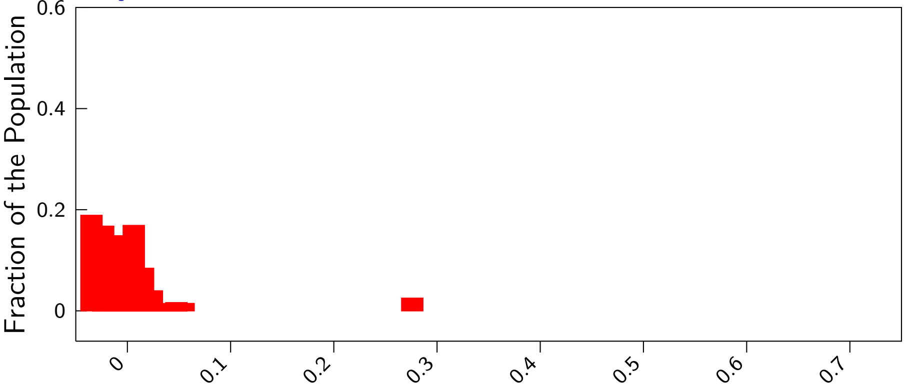

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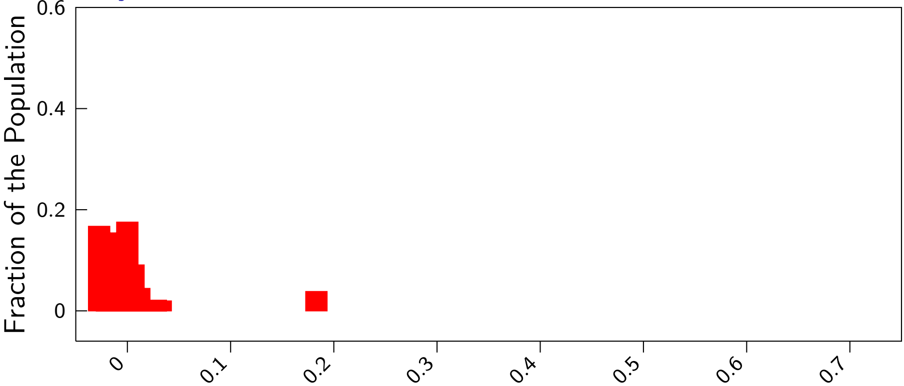

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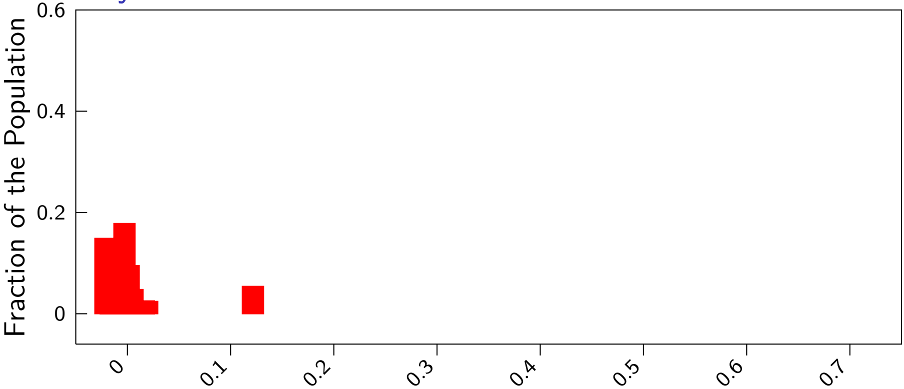

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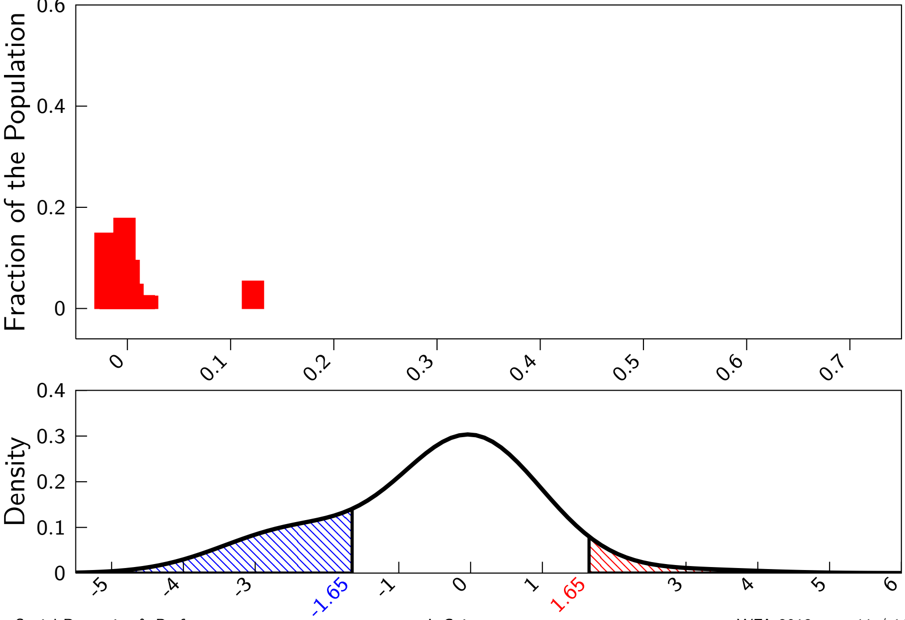

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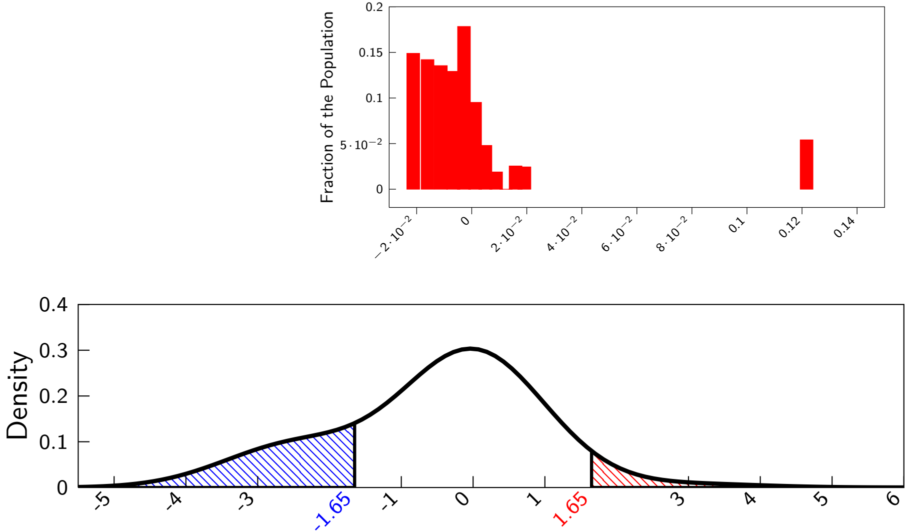

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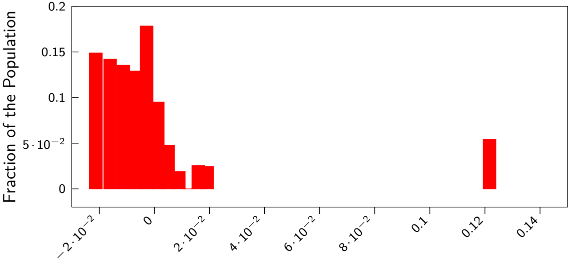

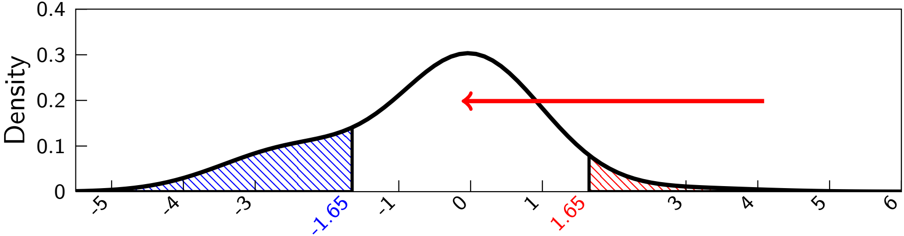

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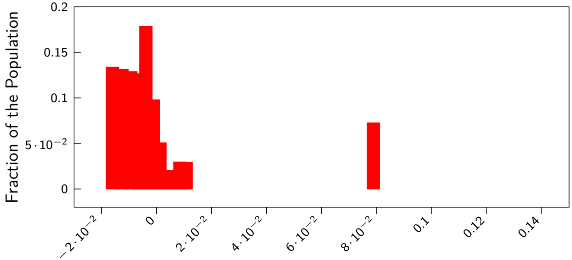

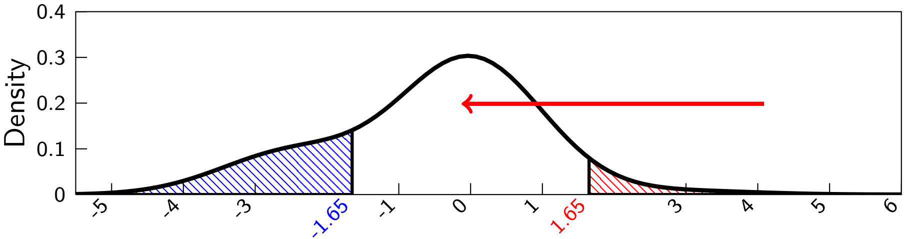

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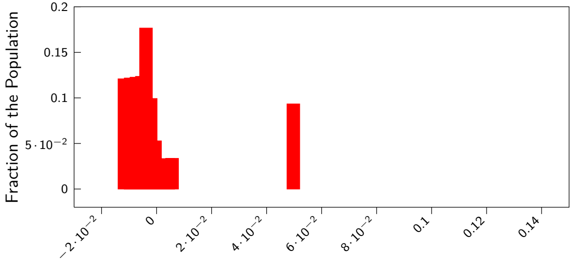

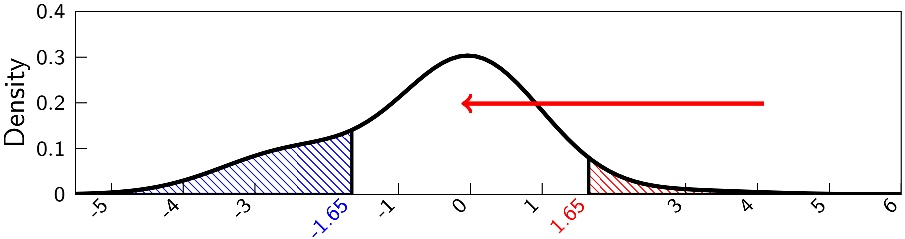

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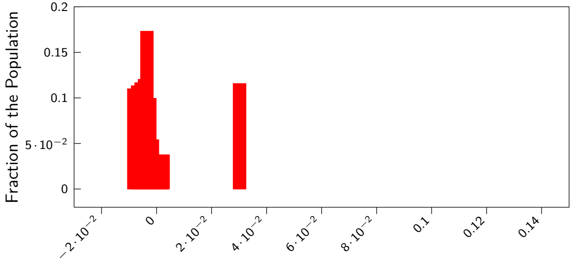

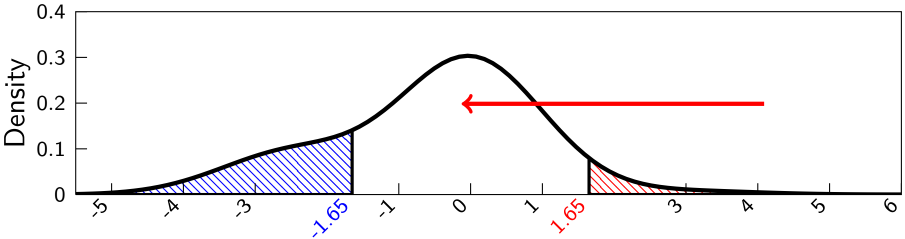

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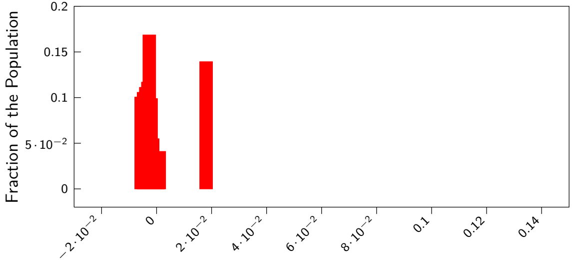

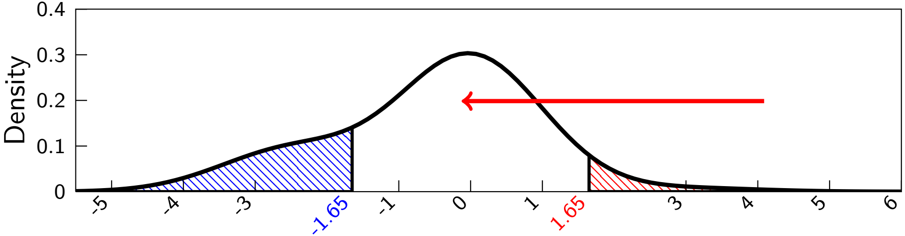

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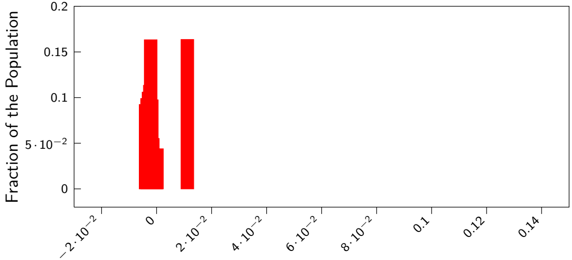

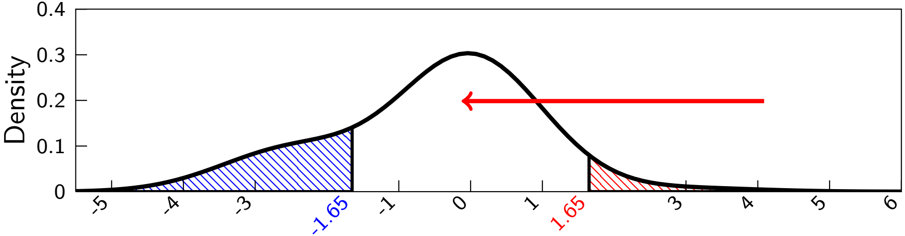

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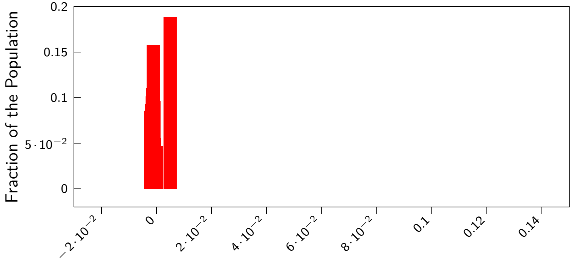

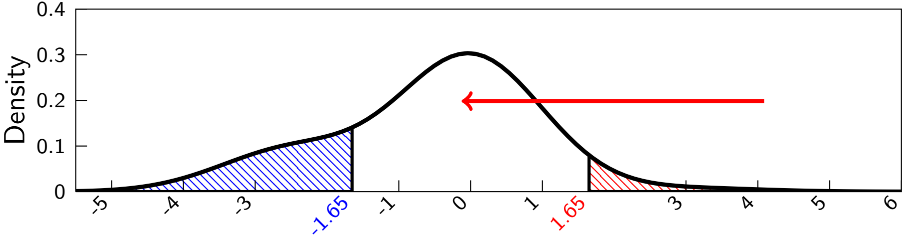

Another Useful Interpretation of Portfolios

A manager l's portfolio can be decomposed as:

$$\theta_t^l - \underbrace{d_{\Theta,t}^l \Theta_t}_{\text{Market-Making}} \equiv \tilde{\theta}_t^l = \underbrace{\frac{\varphi_t^l}{\lambda_{1,t}} E[P_t - E[\Pi + \delta | \mathcal{F}_t^c]|\Pi]}_{\text{a) Loading on Convergence}} + \underbrace{\left(\varphi_t^l - \frac{\lambda_{1,t}}{\lambda_{2,t}} d_{\Theta,t}^l\right) \frac{1}{n_t^l} \sum_{k=1}^{n_t^l} \epsilon_k^l}_{\text{b) Noise from Conversations}}$$

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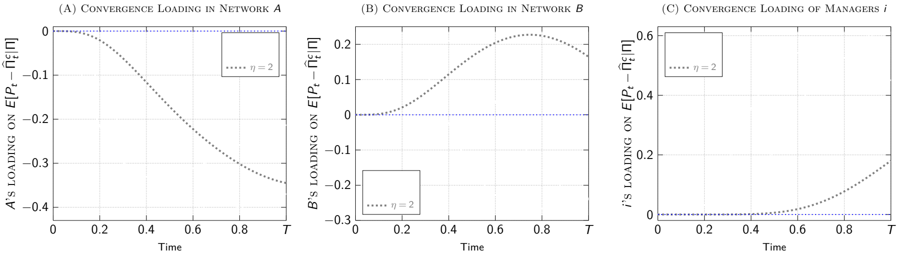

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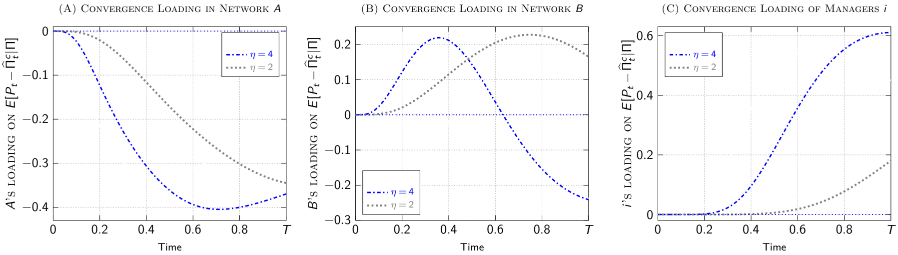

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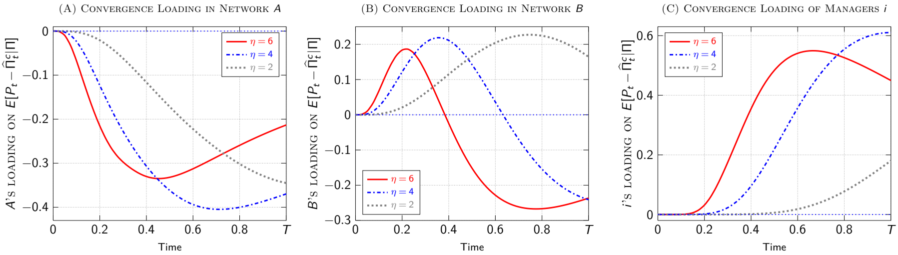

Related Works ▸ Back

Modeling

Andrei and Cujean (2011), Andrei (2012)

Alternative Explanations

Berk and Green (2004)

Related Works ▸ Back

Modeling

Andrei and Cujean (2011), Andrei (2012)

- meetings and trading at the same frequency
- inherently long-lived information
- good ideas stay localized

Alternative Explanations

Berk and Green (2004)

Related Works

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Modeling

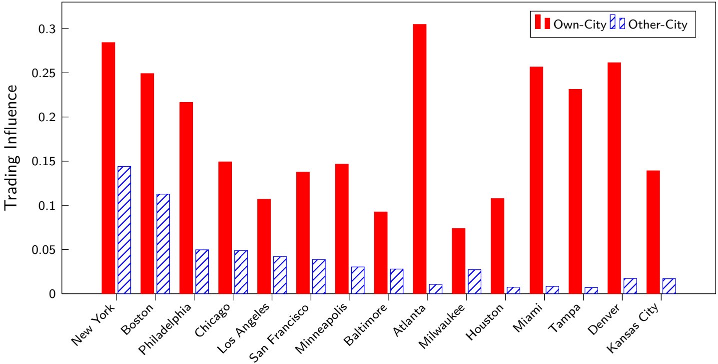
Andrei and Cujean (2011), Andrei (2012)

Alternative Explanations

Berk and Green (2004)

- does not rely on fund flows
- info as the source of managerial ability
- benchmark returns are endogenous

Motivations: ▸ managers interact socially



Sensitivity to a portfolio change in an own/other city

Managers respond more to a portfolio change in their own city

SOURCE: HONG, KUBIK & STEIN (JF, 2005).

Approximation ▸ Back

Introduce a fictitious asset X^I with dynamics $\mathrm{d}X^I = -\eta \mathrm{d}t + \mathrm{d}N_t^I$

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Keep the affine-quadratic setting by a linearization of the jump

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Dualizing: absolute error on V^I is less than 5% (Haugh, Kogan & Wang (2006))

Performance (Market Timing)

$$R_t^I = \alpha_t^I + \beta_t^I \Delta P_t + \gamma_t^I (\Delta P_t)^2 + \epsilon_t^I, \quad \Delta \leq t \leq T - \Delta$$

Treynor-Mazuy

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$$\boxed{R^l_t = \alpha^l_t + \beta^l_t \Delta P_t + \gamma^l_t (\Delta P_t)^2 + \epsilon^l_t, \quad \Delta \leq t \leq T - \Delta}$$

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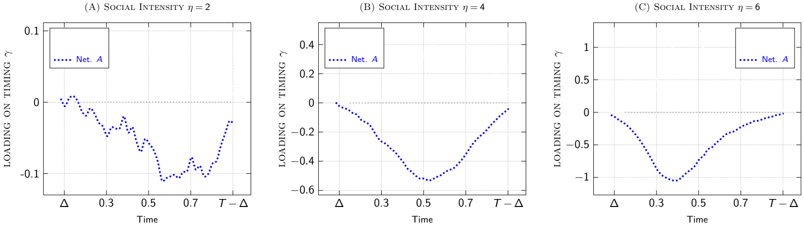

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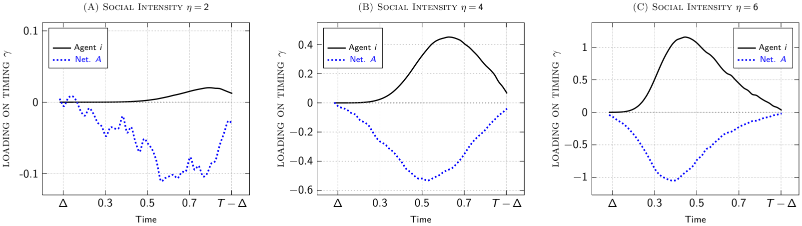

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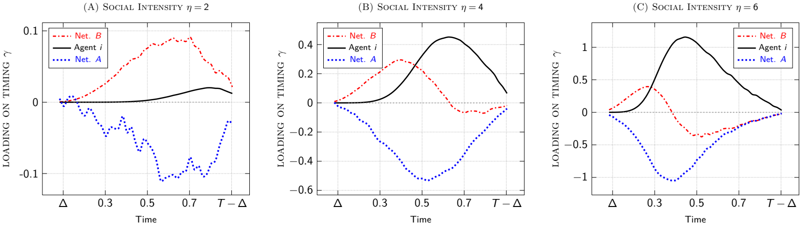

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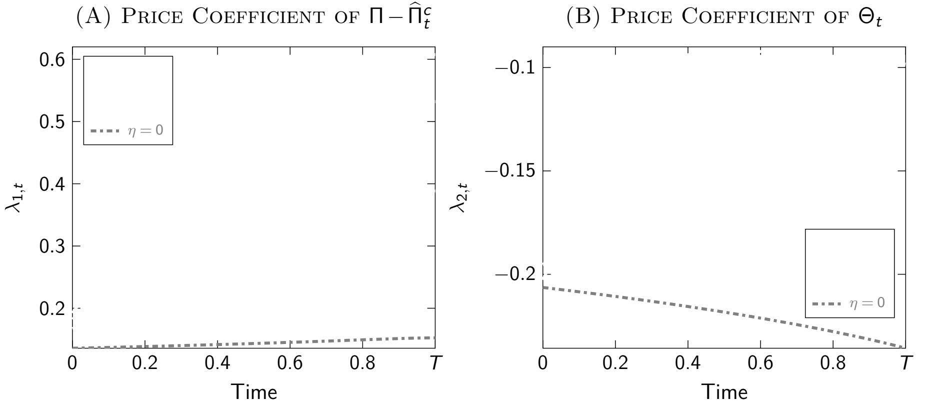
Equilibrium

▸ Equilibrium Price Coefficients

$$P_t = \underbrace{\lambda_{1,t}\Pi + (1-\lambda_{1,t})\widehat{\Pi}_t^c}_{\text{average market expectations}} + \underbrace{\lambda_{2,t}\Theta_t}_{\text{compensation for risk}}$$



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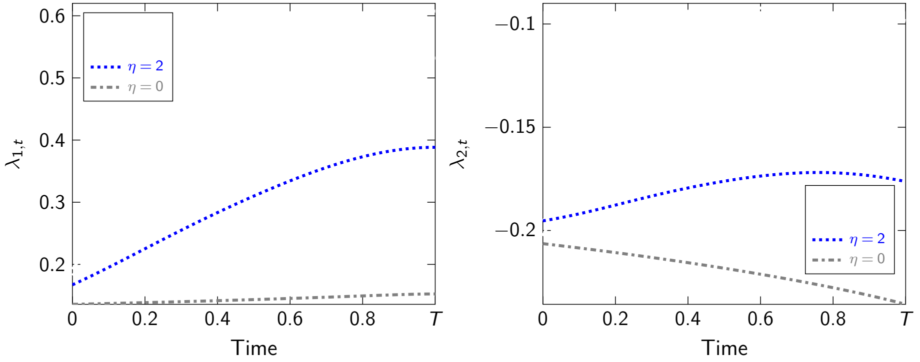

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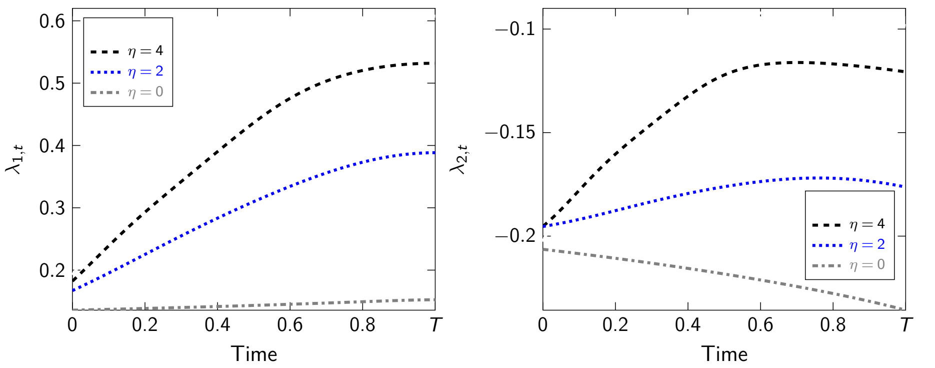

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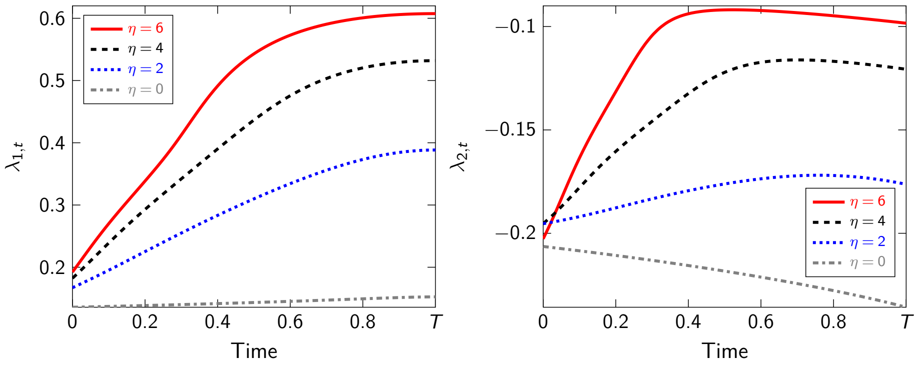

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