

# Hybrid Atlas Model of financial equity market

Tomoyuki Ichiba <sup>1</sup> Ioannis Karatzas <sup>2,3</sup> Adrian Banner <sup>3</sup>  
Vassilios Papathanakos <sup>3</sup> Robert Fernholz <sup>3</sup>

<sup>1</sup> University of California, Santa Barbara <sup>2</sup> Columbia University, New York  
<sup>3</sup> INTECH, Princeton

November 2009

# Outline

Introduction

Hybrid Atlas model

Martingale Problem

Stability

Effective dimension

Rankings

Long-term growth relations

Portfolio analysis

Stochastic Portfolio Theory

Target portfolio

Universal portfolio

Conclusion

## Flow of Capital

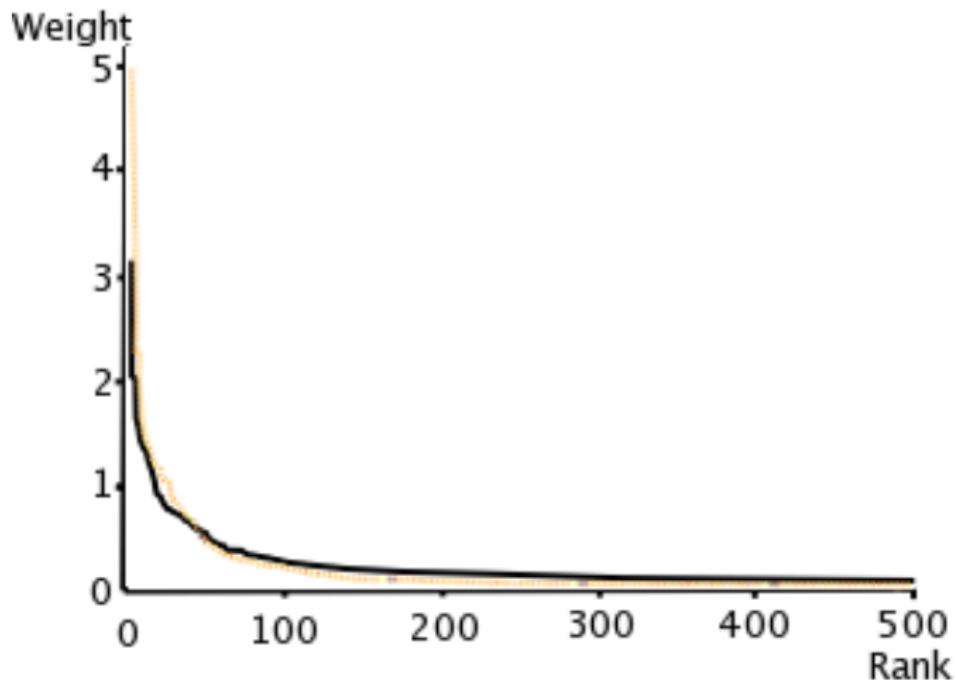


Figure: Capital Distribution Curves (Percentage) for the S&P 500 Index of 1997 (Solid Line) and 1999 (Broken Line).

# Log-Log Capital Distribution Curves

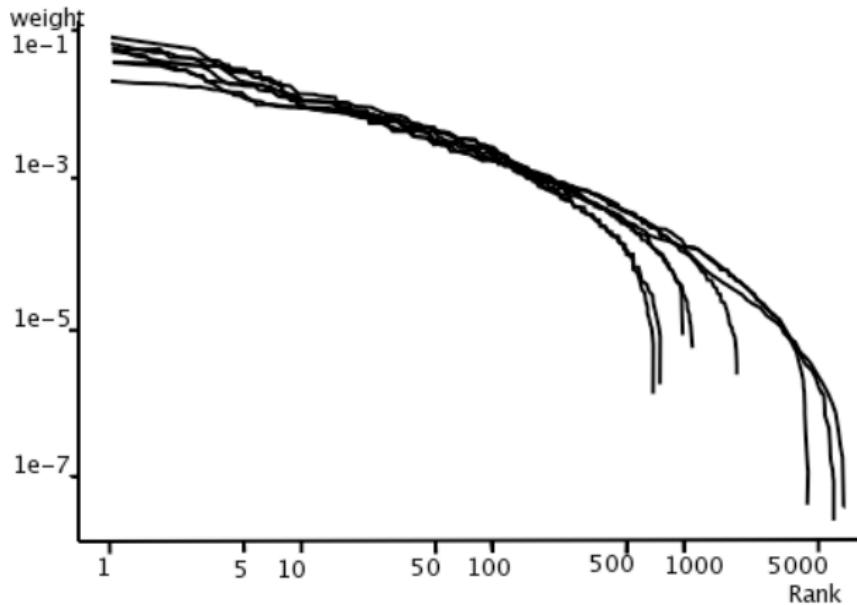


Figure: Capital distribution curves for 1929 (shortest curve) - 1999 (longest curve), every ten years. Source Fernholz('02).

What kind of models can describe this long-term stability?

## A Model of Rankings [Hybrid Atlas model]

- ▶ Capital process  $X := \{(X_1(t), \dots, X_n(t)), 0 \leq t < \infty\}$ .
- ▶ Order Statistics:

$$X_{(1)}(t) \geq \dots \geq X_{(n)}(t); \quad 0 \leq t < \infty.$$

Log capital  $Y := \log X$ :

$$Y_{(1)}(t) \geq \dots \geq Y_{(n)}(t); \quad 0 \leq t < \infty.$$

Dynamics of log capital:

$$d Y_{(k)}(t) = (\gamma + \gamma_i + g_k) d t + \sigma_k d W_i(t) \quad \text{if } Y_{(k)}(t) = Y_i(t);$$

for  $1 \leq i, k \leq n$ ,  $0 \leq t < \infty$ , where  $W(\cdot)$  is  $n$ -dim. B. M.

	company name $i$	$k$ th ranked company *
Drift ("mean")	$\gamma_i$	$g_k$
Diffusion ("variance")		$\sigma_k > 0$

\* Banner, Fernholz & Karatzas ('05), Chatterjee & Pal ('07, '09), Pal & Pitman ('08).

## A Model of Rankings [Hybrid Atlas model]

- ▶ Capital process  $X := \{(X_1(t), \dots, X_n(t)), 0 \leq t < \infty\}$ .
- ▶ Order Statistics:

$$X_{(1)}(t) \geq \dots \geq X_{(n)}(t); \quad 0 \leq t < \infty.$$

Log capital  $Y := \log X$ :

$$Y_{(1)}(t) \geq \dots \geq Y_{(n)}(t); \quad 0 \leq t < \infty.$$

Dynamics of log capital:

$$d Y_{(k)}(t) = (\gamma + \gamma_i + g_k) d t + \sigma_k d W_i(t) \quad \text{if } Y_{(k)}(t) = Y_i(t);$$

for  $1 \leq i, k \leq n$ ,  $0 \leq t < \infty$ , where  $W(\cdot)$  is  $n$ -dim. B. M.

	company name $i$	$k$ th ranked company *
Drift ("mean")	$\gamma_i$	$g_k$
Diffusion ("variance")		$\sigma_k > 0$

\* Banner, Fernholz & Karatzas ('05), Chatterjee & Pal ('07, '09), Pal & Pitman ('08).

## A Model of Rankings [Hybrid Atlas model]

- ▶ Capital process  $X := \{(X_1(t), \dots, X_n(t)), 0 \leq t < \infty\}$ .
- ▶ Order Statistics:

$$X_{(1)}(t) \geq \dots \geq X_{(n)}(t); \quad 0 \leq t < \infty.$$

Log capital  $Y := \log X$ :

$$Y_{(1)}(t) \geq \dots \geq Y_{(n)}(t); \quad 0 \leq t < \infty.$$

Dynamics of log capital:

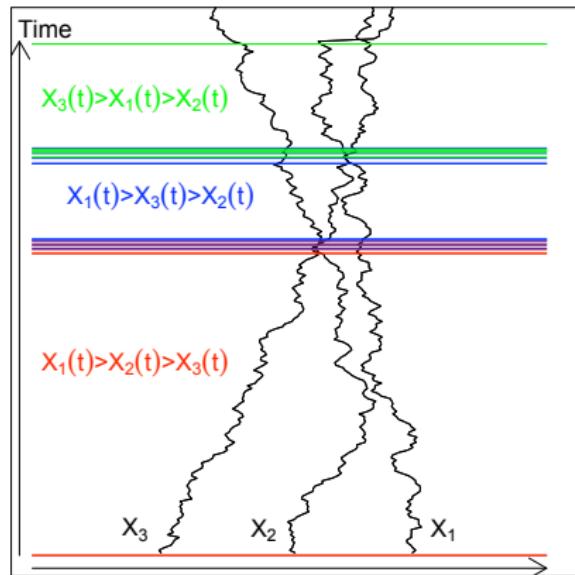
$$d Y_{(k)}(t) = (\gamma + \gamma_i + g_k) d t + \sigma_k d W_i(t) \quad \text{if } Y_{(k)}(t) = Y_i(t);$$

for  $1 \leq i, k \leq n$ ,  $0 \leq t < \infty$ , where  $W(\cdot)$  is  $n$ -dim. B. M.

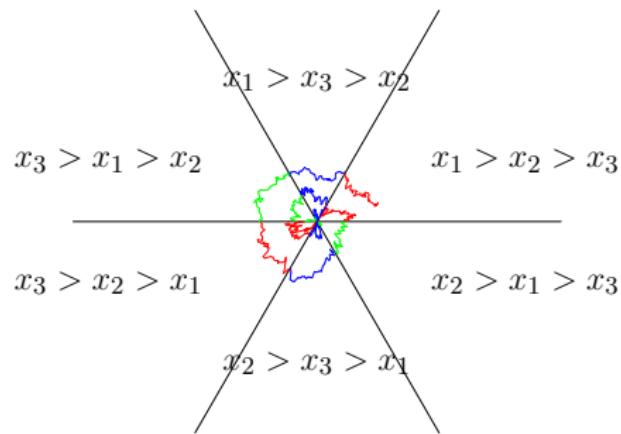
	company name $i$	$k$ th ranked company *
Drift ("mean")	$\gamma_i$	$g_k$
Diffusion ("variance")		$\sigma_k > 0$

\* Banner, Fernholz & Karatzas ('05), Chatterjee & Pal ('07, '09), Pal & Pitman ('08).

# Illustration ( $n = 3$ ) of interactions through rank



Paths in  $\mathbb{R}_+ \times \text{Time}$ .



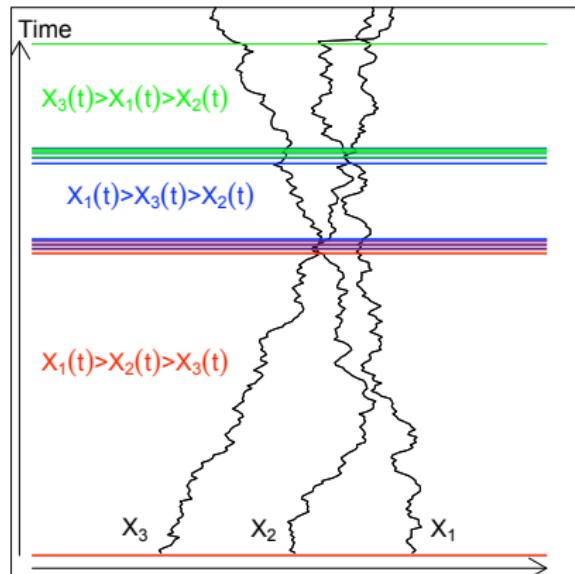
A path in different wedges of  $\mathbb{R}^n$ .

Symmetric group  $\Sigma_n$  of permutations of  $\{1, \dots, n\}$ .

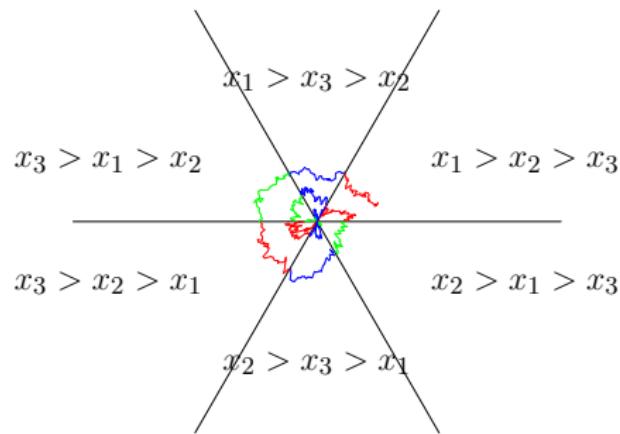
For  $n = 3$ ,

$\{(1, 2, 3), (1, 3, 2), (2, 1, 3), (2, 3, 1), (3, 1, 2), (3, 2, 1)\}$ .

# Illustration ( $n = 3$ ) of interactions through rank



Paths in  $\mathbb{R}_+ \times \text{Time}$ .



A path in different wedges of  $\mathbb{R}^n$ .

Symmetric group  $\Sigma_n$  of permutations of  $\{1, \dots, n\}$ .

For  $n = 3$ ,

$$\{(1, 2, 3), (1, 3, 2), (2, 1, 3), (2, 3, 1), (3, 1, 2), (3, 2, 1)\}.$$

# Vector Representation

$$dY(t) = \textcolor{red}{G}(Y(t))dt + \textcolor{blue}{S}(Y(t))dW(t); \quad 0 \leq t < \infty$$

$\Sigma_n$ : symmetric group of permutations of  $\{1, 2, \dots, n\}$ .

For  $\mathbf{p} \in \Sigma_n$  define wedges (chambers)

$$\mathcal{R}_{\mathbf{p}} := \{x \in \mathbb{R}^n : x_{\mathbf{p}(1)} \geq x_{\mathbf{p}(2)} \geq \dots \geq x_{\mathbf{p}(n)}\}, \quad \mathbb{R}^n = \cup_{\mathbf{p} \in \Sigma_n} \mathcal{R}_{\mathbf{p}},$$

(the inner points of  $\mathcal{R}_{\mathbf{p}}$  and  $\mathcal{R}_{\mathbf{p}'}$  are disjoint for  $\mathbf{p} \neq \mathbf{p}' \in \Sigma_n$ ),

$$\begin{aligned} Q_k^{(i)} &:= \{x \in \mathbb{R}^n : x_i \text{ is ranked } k\text{th among } (x_1, \dots, x_n)\} \\ &= \cup_{\{\mathbf{p} : \mathbf{p}(k)=i\}} \mathcal{R}_{\mathbf{p}}; \quad 1 \leq i, k \leq n, \end{aligned}$$

$$\cup_{j=1}^n Q_k^{(j)} = \mathbb{R}^n = \cup_{\ell=1}^n Q_{\ell}^{(i)} \text{ and } \mathcal{R}_{\mathbf{p}} = \cap_{k=1}^n Q_k^{(\mathbf{p}(k))}.$$

$$\begin{aligned} \textcolor{red}{G}(y) &= \sum_{\mathbf{p} \in \Sigma_n} (g_{\mathbf{p}^{-1}(1)} + \gamma_1 + \gamma, \dots, g_{\mathbf{p}^{-1}(n)} + \gamma_n + \gamma)' \cdot \mathbf{1}_{\mathcal{R}_{\mathbf{p}}}(y), \\ \textcolor{blue}{S}(y) &= \sum_{\mathbf{p} \in \Sigma_n} \underbrace{\text{diag}(\sigma_{\mathbf{p}^{-1}(1)}, \dots, \sigma_{\mathbf{p}^{-1}(n)})}_{\mathfrak{s}_{\mathbf{p}}} \cdot \mathbf{1}_{\mathcal{R}_{\mathbf{p}}}(y); \quad y \in \mathbb{R}^n. \end{aligned}$$

# Vector Representation

$$dY(t) = \textcolor{red}{G}(Y(t))dt + \textcolor{blue}{S}(Y(t))dW(t); \quad 0 \leq t < \infty$$

$\Sigma_n$ : symmetric group of permutations of  $\{1, 2, \dots, n\}$ .

For  $\mathbf{p} \in \Sigma_n$  define wedges (chambers)

$$\mathcal{R}_{\mathbf{p}} := \{x \in \mathbb{R}^n : x_{\mathbf{p}(1)} \geq x_{\mathbf{p}(2)} \geq \dots \geq x_{\mathbf{p}(n)}\}, \quad \mathbb{R}^n = \cup_{\mathbf{p} \in \Sigma_n} \mathcal{R}_{\mathbf{p}},$$

(the inner points of  $\mathcal{R}_{\mathbf{p}}$  and  $\mathcal{R}_{\mathbf{p}'}$  are disjoint for  $\mathbf{p} \neq \mathbf{p}' \in \Sigma_n$ ),

$$\begin{aligned} Q_k^{(i)} &:= \{x \in \mathbb{R}^n : x_i \text{ is ranked } k\text{th among } (x_1, \dots, x_n)\} \\ &= \cup_{\{\mathbf{p} : \mathbf{p}(k)=i\}} \mathcal{R}_{\mathbf{p}}; \quad 1 \leq i, k \leq n, \end{aligned}$$

$$\cup_{j=1}^n Q_k^{(j)} = \mathbb{R}^n = \cup_{\ell=1}^n Q_{\ell}^{(i)} \text{ and } \mathcal{R}_{\mathbf{p}} = \cap_{k=1}^n Q_k^{(\mathbf{p}(k))}.$$

$$\begin{aligned} \textcolor{red}{G}(y) &= \sum_{\mathbf{p} \in \Sigma_n} (g_{\mathbf{p}^{-1}(1)} + \gamma_1 + \gamma, \dots, g_{\mathbf{p}^{-1}(n)} + \gamma_n + \gamma)' \cdot \mathbf{1}_{\mathcal{R}_{\mathbf{p}}}(y), \\ \textcolor{blue}{S}(y) &= \sum_{\mathbf{p} \in \Sigma_n} \underbrace{\text{diag}(\sigma_{\mathbf{p}^{-1}(1)}, \dots, \sigma_{\mathbf{p}^{-1}(n)})}_{\mathfrak{s}_{\mathbf{p}}} \cdot \mathbf{1}_{\mathcal{R}_{\mathbf{p}}}(y); \quad y \in \mathbb{R}^n. \end{aligned}$$

# Martingale Problem

**Theorem** [Krylov('71), Stroock & Varadhan('79) , Bass & Pardoux('87)] Suppose that the coefficients  $G(\cdot)$  and  $a(\cdot) := SS'(\cdot)$  are bounded and measurable, and that  $a(\cdot)$  is uniformly positive-definite and piecewise constant in each wedge. For each  $y_0 \in \mathbb{R}^n$  there is a **unique one** probability measure  $\mathbb{P}$  on  $C([0, \infty), \mathbb{R}^n)$  such that  $\mathbb{P}(Y_0 = y_0) = 1$  and

$$f(Y_t) - f(Y_0) - \int_0^t L f(Y_s) \, ds; \quad 0 \leq t < \infty$$

is a  $\mathbb{P}$  local martingale for every  $f \in C^2(\mathbb{R}^2)$  where

$$L f(x) = \frac{1}{2} \sum_{i,j=1}^n a_{ij}(x) D_{ij} f(x) + \sum_{i=1}^n G_i(x) D_i f(x); \quad x \in \mathbb{R}^n.$$

This implies that the hybrid Atlas model is **well-defined**.

## Model

Market capitalization  $X$  follows **Hybrid Atlas** model: the log capitalization  $Y_i = \log X_i$  of company  $i$  has

drift  $\gamma + g_k + \gamma_i$  and volatility  $\sigma_k$ ,

when company  $i$  is  $k^{\text{th}}$ ranked, i.e.,  $Y \in Q_k^{(i)}$  for  $1 \leq k, i \leq n$ .

$$\begin{aligned} d Y_i(t) &= \left( \gamma + \sum_{k=1}^n g_k \mathbf{1}_{Q_k^{(i)}}(Y(t)) + \gamma_i \right) d t \\ &\quad + \sum_{k=1}^n \sigma_k \mathbf{1}_{Q_k^{(i)}}(Y(t)) d W_i(t); \quad 0 \leq t < \infty. \end{aligned}$$

## Model assumptions

Market capitalization  $X$  follows **Hybrid Atlas** model: the log capitalization  $Y_i = \log X_i$  of company  $i$  has

drift  $\gamma + g_k + \gamma_i$  and volatility  $\sigma_k$ ,

when company  $i$  is  $k^{\text{th}}$  ranked, i.e.,  $Y \in Q_k^{(i)}$  for  $1 \leq k, i \leq n$ .  
Assume  $\sigma_k > 0$ ,  $(g_k, 1 \leq k \leq n)$ ,  $(\gamma_i, 1 \leq i \leq n)$  and  $\gamma$  are real constants with stability conditions

$$\sum_{k=1}^n g_k + \sum_{i=1}^n \gamma_i = 0, \quad \sum_{\ell=1}^k (g_\ell + \gamma_{\mathbf{p}(\ell)}) < 0, \quad k = 1, \dots, n-1, \quad \mathbf{p} \in \Sigma_n.$$

- ▶  $\gamma_i = 0, 1 \leq i \leq n, \quad g_1 = \dots = g_{n-1} = -g < 0,$   
 $g_n = (n-1)g > 0.$
- ▶  $\gamma_i = 1 - (2i)/(n+1), 1 \leq i \leq n,$   
 $g_k = -1, k = 1, \dots, n-1, \quad g_n = n-1.$

## Model assumptions

Market capitalization  $X$  follows **Hybrid Atlas** model: the log capitalization  $Y_i = \log X_i$  of company  $i$  has

drift  $\gamma + g_k + \gamma_i$  and volatility  $\sigma_k$ ,

when company  $i$  is  $k^{\text{th}}$ ranked, i.e.,  $Y \in Q_k^{(i)}$  for  $1 \leq k, i \leq n$ .  
Assume  $\sigma_k > 0$ ,  $(g_k, 1 \leq k \leq n)$ ,  $(\gamma_i, 1 \leq i \leq n)$  and  $\gamma$  are real constants with **stability conditions**

$$\sum_{k=1}^n g_k + \sum_{i=1}^n \gamma_i = 0, \quad \sum_{\ell=1}^k (g_\ell + \gamma_{\mathbf{p}(\ell)}) < 0, \quad k = 1, \dots, n-1, \quad \mathbf{p} \in \Sigma_n.$$

- ▶  $\gamma_i = 0, 1 \leq i \leq n, \quad g_1 = \dots = g_{n-1} = -g < 0,$   
 $g_n = (n-1)g > 0.$
- ▶  $\gamma_i = 1 - (2i)/(n+1), 1 \leq i \leq n,$   
 $g_k = -1, k = 1, \dots, n-1, \quad g_n = n-1.$

## Model assumptions

Market capitalization  $X$  follows **Hybrid Atlas** model: the log capitalization  $Y_i = \log X_i$  of company  $i$  has

drift  $\gamma + g_k + \gamma_i$  and volatility  $\sigma_k$ ,

when company  $i$  is  $k^{\text{th}}$ ranked, i.e.,  $Y \in Q_k^{(i)}$  for  $1 \leq k, i \leq n$ .  
Assume  $\sigma_k > 0$ ,  $(g_k, 1 \leq k \leq n)$ ,  $(\gamma_i, 1 \leq i \leq n)$  and  $\gamma$  are real constants with **stability conditions**

$$\sum_{k=1}^n g_k + \sum_{i=1}^n \gamma_i = 0, \quad \sum_{\ell=1}^k (g_\ell + \gamma_{\mathbf{p}(\ell)}) < 0, \quad k = 1, \dots, n-1, \quad \mathbf{p} \in \Sigma_n.$$

- ▶  $\gamma_i = 0, 1 \leq i \leq n, \quad g_1 = \dots = g_{n-1} = -g < 0,$   
 $g_n = (n-1)g > 0.$
- ▶  $\gamma_i = 1 - (2i)/(n+1), 1 \leq i \leq n,$   
 $g_k = -1, k = 1, \dots, n-1, \quad g_n = n-1.$

## Model Summary

The log-capitalization  $Y = \log X$  follows

$$\begin{aligned} d Y_i(t) &= \left( \gamma + \sum_{k=1}^n g_k \mathbf{1}_{Q_k^{(i)}}(Y(t)) + \gamma_i \right) d t \\ &\quad + \sum_{k=1}^n \sigma_k \mathbf{1}_{Q_k^{(i)}}(Y(t)) d W_i(t); \quad 0 \leq t < \infty \end{aligned}$$

where  $\sigma_k > 0$ ,  $(g_k, 1 \leq k \leq n)$ ,  $(\gamma_i, 1 \leq i \leq n)$  and  $\gamma$  are real constants with **stability conditions**

$$\sum_{k=1}^n g_k + \sum_{i=1}^n \gamma_i = 0, \quad \sum_{\ell=1}^k (g_\ell + \gamma_{\mathbf{p}(\ell)}) < 0, \quad k = 1, \dots, n-1, \quad \mathbf{p} \in \Sigma_n.$$

## Stochastic stability

The average  $\bar{Y}(\cdot) := \sum_{i=1}^n Y_i(\cdot) / n$  of log-capitalization:

$$d\bar{Y}(t) = \gamma dt + \frac{1}{n} \sum_{k=1}^n \sigma_k \underbrace{\sum_{i=1}^n \mathbf{1}_{Q_k^{(i)}}(Y(t)) dW_i(t)}_{dB_k(t)}$$

is a Brownian motion with variance rate  $\sum_{k=1}^n \sigma_k^2/n^2$  drift  $\gamma$  by the Dambis-Dubins-Schwartz Theorem.

**Proposition** Under the assumptions the deviations  $\tilde{Y}(\cdot) := (Y_1(\cdot) - \bar{Y}(\cdot), \dots, Y_n(\cdot) - \bar{Y}(\cdot))$  from the average are stable in distribution, i.e., there is a unique invariant probability measure  $\mu(\cdot)$  such that for every bounded, measurable function  $f$  we have the **Strong Law of Large Numbers**

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T f(\tilde{Y}(t)) dt = \int_{\Pi} f(y) \mu(dy), \quad a.s.$$

where  $\Pi := \{y \in \mathbb{R}^n : y_1 + \dots + y_n = 0\}$ .

## Stochastic stability

The average  $\bar{Y}(\cdot) := \sum_{i=1}^n Y_i(\cdot) / n$  of log-capitalization:

$$d\bar{Y}(t) = \gamma dt + \frac{1}{n} \sum_{k=1}^n \sigma_k \underbrace{\sum_{i=1}^n \mathbf{1}_{Q_k^{(i)}}(Y(t)) dW_i(t)}_{dB_k(t)}$$

is a Brownian motion with variance rate  $\sum_{k=1}^n \sigma_k^2/n^2$  drift  $\gamma$  by the Dambis-Dubins-Schwartz Theorem.

**Proposition** Under the assumptions the deviations  $\tilde{Y}(\cdot) := (Y_1(\cdot) - \bar{Y}(\cdot), \dots, Y_n(\cdot) - \bar{Y}(\cdot))$  from the average are stable in distribution, i.e., there is a unique invariant probability measure  $\mu(\cdot)$  such that for every bounded, measurable function  $f$  we have the **Strong Law of Large Numbers**

$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T f(\tilde{Y}(t)) dt = \int_{\Pi} f(y) \mu(dy), \quad a.s.$$

where  $\Pi := \{y \in \mathbb{R}^n : y_1 + \dots + y_n = 0\}$ .

## Average occupation times

Especially taking  $f(\cdot) = \mathbf{1}_{\mathcal{R}_\mathbf{p}}(\cdot)$  or  $\mathbf{1}_{Q_k^{(i)}}(\cdot)$ , we define from  $\mu$  the **average occupation time** of  $X$  in  $\mathcal{R}_\mathbf{p}$  or  $Q_k^{(i)}$ :

$$\theta_\mathbf{p} := \mu(\mathcal{R}_\mathbf{p}) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T \mathbf{1}_{\mathcal{R}_\mathbf{p}}(X(t)) dt$$

$$\theta_{k,i} := \mu(Q_k^{(i)}) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T \mathbf{1}_{Q_k^{(i)}}(X(t)) dt, \quad 1 \leq k, i \leq n,$$

since  $\mathbf{1}_{\mathcal{R}_\mathbf{p}}(\tilde{Y}(\cdot)) = \mathbf{1}_{\mathcal{R}_\mathbf{p}}(X(\cdot))$  and  $\mathbf{1}_{Q_k^{(i)}}(X(\cdot)) = \mathbf{1}_{Q_k^{(i)}}(\tilde{Y}(\cdot))$ . By definition

- ▶  $0 \leq \theta_{k,i} = \sum_{\{\mathbf{p} \in \Sigma_n : \mathbf{p}(k) = i\}} \theta_\mathbf{p} \leq 1$  for  $1 \leq k, i \leq n$ ,
- ▶  $\sum_{\ell=1}^n \theta_{\ell,i} = \sum_{j=1}^n \theta_{k,j} = 1$  for  $1 \leq k, i \leq n$ .

What is the invariant distribution  $\mu$ ?

## Attainability

- ▶ One-dimensional Brownian motion attains the origin infinitely often.
- ▶ Two-dimensional Brownian motion does not attain the origin.

Does the process  $X(\cdot)$  attain the origin?

$$X(t) = X(0) + \int_0^t b(X(s)) ds + \int_0^t \sigma(X(s)) dW(s)$$

where  $b$  and  $\sigma$  are bounded measurable functions.

- ▶ Friedman('74), Bass & Pardoux('87).

# Effective Dimension

Let us define *effective dimension*  $\text{ED}(\cdot)$  by

$$\text{ED}(x) = \frac{\text{trace}(A(x))\|x\|^2}{x'A(x)x}; \quad x \in \mathbb{R}^n \setminus \{0\},$$

where  $A(\cdot) = \sigma(\cdot)\sigma(\cdot)'$ .

## Proposition

Suppose  $X(0) \neq 0$ .

If  $\inf_{x \in \mathbb{R}^n \setminus \{0\}} \text{ED}(x) \geq 2$ , then  $X(\cdot)$  does not attain the origin.

If  $\sup_{x \in \mathbb{R}^n \setminus \{0\}} \text{ED}(x) < 2$  and if there is no drift, i.e.,  $b(\cdot) \equiv 0$ , then  $X(\cdot)$  attains the origin.

- ▶ Exterior Dirichlet Problem by Meyers and Serrin('60).
- ▶ Removal of drift by Girsanov's theorem.
- ▶ If there is drift, take  $\frac{[\text{trace}(A(x))+x'b(x)] \cdot \|x\|^2}{x'A(x)x}$ .

## Triple collision

Now consider *triple collision*:

$$\{X_i(t) = X_j(t) = X_k(t) \text{ for some } t > 0, \quad 1 \leq i < j < k \leq n\}.$$

What is the probability of triple collision?

Fix  $i = 1, j = 2, k = 3$ . Let us define the sum of squared distances:

$$s^2(x) := (x_1 - x_2)^2 + (x_2 - x_3)^2 + (x_3 - x_1)^2 = x' D D' x; \quad x \in \mathbb{R}^n,$$

where  $(n \times 3)$  matrix  $D$  is defined by  $D := (d_1, d_2, d_3)$  with

$$\begin{aligned} d_1 &:= (1, -1, 0, \dots, 0)', & d_2 &:= (0, 1, -1, 0, \dots, 0)', \\ d_3 &:= (-1, 0, 1, \dots, 0)'. \end{aligned}$$

$$\mathcal{Z} := \{x \in \mathbb{R}^n : s(x) = 0\}.$$

Define the **local** effective dimension:

$$R(x) := \frac{\text{trace}(D'A(x)D) x' D D' x}{x' D D' A(x) D D' x} ; \quad x \in \mathbb{R}^n \setminus \mathcal{Z} .$$

### Proposition

Suppose  $s(X(0)) \neq 0$ . If  $\inf_{x \in \mathbb{R}^n \setminus \mathcal{Z}} R(x) \geq 2$ , then

$$\mathbb{P}(X_1(t) = X_2(t) = X_3(t) \text{ for some } t \geq 0) = 0.$$

If  $\sup_{x \in \mathbb{R}^n \setminus \mathcal{Z}} R(x) < 2$  and if there is no drift, i.e.,  $b(\cdot) \equiv 0$ , then

$$\mathbb{P}(X_1(t) = X_2(t) = X_3(t) \text{ for some } t \geq 0) = 1.$$

- ▶  $R(\cdot) \equiv 2$  for  $n$ -dim. BM, i.e.,  $A(\cdot) \equiv I$ .
- ▶ If there is drift, take  $\frac{[\text{trace}(D'A(x)D) + x' D D' b(x)] \cdot x' D D' x}{x' D D' A(x) D D' x}$ .

Idea of Proof: a comparison with Bessel process with dimension two.

Define the **local** effective dimension:

$$R(x) := \frac{\text{trace}(D'A(x)D) \cdot x' D D' x}{x' D D' A(x) D D' x} ; \quad x \in \mathbb{R}^n \setminus \mathcal{Z} .$$

### Proposition

Suppose  $s(X(0)) \neq 0$ . If  $\inf_{x \in \mathbb{R}^n \setminus \mathcal{Z}} R(x) \geq 2$ , then

$$\mathbb{P}(X_1(t) = X_2(t) = X_3(t) \text{ for some } t \geq 0) = 0.$$

If  $\sup_{x \in \mathbb{R}^n \setminus \mathcal{Z}} R(x) < 2$  and if there is no drift, i.e.,  $b(\cdot) \equiv 0$ , then

$$\mathbb{P}(X_1(t) = X_2(t) = X_3(t) \text{ for some } t \geq 0) = 1.$$

- ▶  $R(\cdot) \equiv 2$  for  $n$ -dim. BM, i.e.,  $A(\cdot) \equiv I$ .
- ▶ If there is drift, take  $\frac{[\text{trace}(D'A(x)D) + x' D D' b(x)] \cdot x' D D' x}{x' D D' A(x) D D' x}$ .

Idea of Proof: a comparison with Bessel process with dimension two.

Define the **local** effective dimension:

$$R(x) := \frac{\text{trace}(D'A(x)D) \cdot x' D D' x}{x' D D' A(x) D D' x} ; \quad x \in \mathbb{R}^n \setminus \mathcal{Z} .$$

### Proposition

Suppose  $s(X(0)) \neq 0$ . If  $\inf_{x \in \mathbb{R}^n \setminus \mathcal{Z}} R(x) \geq 2$ , then

$$\mathbb{P}(X_1(t) = X_2(t) = X_3(t) \text{ for some } t \geq 0) = 0.$$

If  $\sup_{x \in \mathbb{R}^n \setminus \mathcal{Z}} R(x) < 2$  and if there is no drift, i.e.,  $b(\cdot) \equiv 0$ , then

$$\mathbb{P}(X_1(t) = X_2(t) = X_3(t) \text{ for some } t \geq 0) = 1.$$

- ▶  $R(\cdot) \equiv 2$  for  $n$ -dim. BM, i.e.,  $A(\cdot) \equiv I$ .
- ▶ If there is drift, take  $\frac{\text{trace}(D'A(x)D) + x' D D' b(x)] \cdot x' D D' x}{x' D D' A(x) D D' x}$ .

Idea of Proof: a comparison with Bessel process with dimension two.

# Rankings

Recall  $Y_{(1)}(\cdot) \geq Y_{(2)}(\cdot) \geq \cdots \geq Y_{(n)}(\cdot)$ . Let us denote by  $\Lambda^{k,j}(t)$  the local time accumulated at the origin by the nonnegative semimartingale  $Y_{(k)}(\cdot) - Y_{(j)}(\cdot)$  up to time  $t$  for  $1 \leq k < j \leq n$ .

**Theorem** [Banner & Ghomrasni (07)] For a general class of semimartingale  $Y(\cdot)$ , the rankings satisfy

$$\begin{aligned} d Y_{(k)}(t) &= \sum_{i=1}^n \mathbf{1}_{Q_k^{(i)}}(Y(t)) d Y_i(t) \\ &\quad + (N_k(t))^{-1} \left[ \sum_{\ell=k+1}^n d \Lambda^{k,\ell}(t) - \sum_{\ell=1}^{k-1} d \Lambda^{\ell,k}(t) \right] \end{aligned}$$

where  $N_k(t)$  is the cardinality  $|\{i : Y_i(t) = Y_{(k)}(t)\}|$ .

## Rankings

Recall  $Y_{(1)}(\cdot) \geq Y_{(2)}(\cdot) \geq \cdots \geq Y_{(n)}(\cdot)$ . Let us denote by  $\Lambda^{k,j}(t)$  the local time accumulated at the origin by the nonnegative semimartingale  $Y_{(k)}(\cdot) - Y_{(j)}(\cdot)$  up to time  $t$  for  $1 \leq k < j \leq n$ .

**Lemma** Under the non-degeneracy condition  $\sigma_k > 0$  for  $k = 1, \dots, n$ ,

$$\begin{aligned} dY_{(k)}(t) &= \left( \gamma + g_k + \sum_{i=1}^n \gamma_i 1_{Q_k^{(i)}}(Y(t)) \right) dt + \sigma_k dB_k(t) \\ &\quad + \frac{1}{2} \left[ d\Lambda^{k,k+1}(t) - d\Lambda^{k-1,k}(t) \right]. \end{aligned}$$

for  $k = 1, \dots, n$ ,  $0 \leq t \leq T$ .

Idea of Proof: a comparison with a Bessel process with dimension one to show  $\Lambda^{k,\ell}(\cdot) \equiv 0$ ,  $|k - \ell| \geq 2$ .

## Rankings

Recall  $Y_{(1)}(\cdot) \geq Y_{(2)}(\cdot) \geq \cdots \geq Y_{(n)}(\cdot)$ . Let us denote by  $\Lambda^{k,j}(t)$  the local time accumulated at the origin by the nonnegative semimartingale  $Y_{(k)}(\cdot) - Y_{(j)}(\cdot)$  up to time  $t$  for  $1 \leq k < j \leq n$ .

**Lemma** Under the non-degeneracy condition  $\sigma_k > 0$  for  $k = 1, \dots, n$ ,

$$\begin{aligned} dY_{(k)}(t) &= \left( \gamma + g_k + \sum_{i=1}^n \gamma_i 1_{Q_k^{(i)}}(Y(t)) \right) dt + \sigma_k dB_k(t) \\ &\quad + \frac{1}{2} \left[ d\Lambda^{k,k+1}(t) - d\Lambda^{k-1,k}(t) \right]. \end{aligned}$$

for  $k = 1, \dots, n$ ,  $0 \leq t \leq T$ .

Idea of Proof: a comparison with a Bessel process with dimension **one** to show  $\Lambda^{k,\ell}(\cdot) \equiv 0$ ,  $|k - \ell| \geq 2$ .

## Long-term growth relations

**Proposition** Under the assumptions we obtain the following long-term growth relations:

$$\begin{aligned}\lim_{T \rightarrow \infty} \frac{Y_i(T)}{T} &= \lim_{T \rightarrow \infty} \frac{\log X_i(T)}{T} = \gamma \\ &= \lim_{T \rightarrow \infty} \frac{\log \sum_{i=1}^n X_i(T)}{T} \quad a.s.\end{aligned}$$

Thus the model is coherent:

$$\lim_{T \rightarrow \infty} \frac{1}{T} \log \mu_i(T) = 0 \quad a.s.; \quad i = 1, \dots, n$$

where  $\mu_i(\cdot) = X_i(\cdot) / (X_1(\cdot) + \dots + X_n(\cdot))$ . Moreover,

$$\sum_{k=1}^n g_k \theta_{k,i} + \gamma_i = 0; \quad i = 1, \dots, n.$$

$$\sum_{k=1}^n \textcolor{blue}{g_k} \theta_{k,i} + \textcolor{blue}{\gamma_i} = 0; \quad i = 1, \dots, n.$$

The log-capitalization  $Y$  grows with rate  $\textcolor{red}{\gamma}$  and follows

$$d Y_i(t) = \left( \textcolor{red}{\gamma} + \sum_{k=1}^n \textcolor{blue}{g_k} \mathbf{1}_{Q_k^{(i)}}(Y(t)) + \textcolor{blue}{\gamma_i} \right) d t \\ + \sum_{k=1}^n \sigma_k \mathbf{1}_{Q_k^{(i)}}(Y(t)) d W_i(t); \quad 0 \leq t < \infty$$

for  $i = 1, \dots, n$ . The ranking  $(Y_{(1)}(\cdot), \dots, Y_{(n)}(\cdot))$  follows

$$d Y_{(k)}(t) = \left( \gamma + g_k + \sum_{i=1}^n \gamma_i \mathbf{1}_{Q_k^{(i)}}(Y(t)) \right) d t + \sigma_k d B_k(t) \\ + \frac{1}{2} \left[ d \Lambda^{k,k+1}(t) - d \Lambda^{k-1,k}(t) \right].$$

for  $k = 1, \dots, n$ ,  $0 \leq t < \infty$ .

# Semimartingale reflected Brownian motions

The adjacent differences (gaps)  $\Xi(\cdot) := (\Xi_1(\cdot), \dots, \Xi_n(\cdot))'$   
where  $\Xi_k(\cdot) := Y_{(k)}(\cdot) - Y_{(k+1)}(\cdot)$  for  $k = 1, \dots, n-1$  can be  
seen as a semimartingale reflected Brownian motion (SRBM):

$$\Xi(t) = \Xi(0) + \zeta(t) + (I_n - \mathfrak{Q})\Lambda(t)$$

where  $\zeta(\cdot) := (\zeta_1(\cdot), \dots, \zeta_n(\cdot))'$ ,  $\Lambda(\cdot) := (\Lambda^{1,2}(\cdot), \dots, \Lambda^{n-1,n}(\cdot))'$ ,

$$\zeta_k(\cdot) := \sum_{i=1}^n \int_0^\cdot \mathbf{1}_{Q_k^{(i)}}(Y(s)) dY(s) - \sum_{i=1}^n \int_0^\cdot \mathbf{1}_{Q_{k+1}^{(i)}}(Y(s)) dY(s)$$

for  $k = 1, \dots, n-1$ , and  $\mathfrak{Q}$  is an  $(n-1) \times (n-1)$  matrix with  
elements

$$\mathfrak{Q} := \begin{pmatrix} 0 & 1/2 & & \\ 1/2 & 0 & 1/2 & \\ & 1/2 & \ddots & \ddots \\ & \ddots & 0 & 1/2 \\ & & 1/2 & 0 \end{pmatrix}.$$

Thus the gaps  $\Xi_k := Y_{(k)}(\cdot) - Y_{(k+1)}(\cdot)$  follow

$$\Xi(t) = \Xi(0) + \underbrace{\zeta(t)}_{\text{semimartingale}} + \underbrace{(I_n - \mathfrak{Q})\Lambda(t)}_{\text{reflection part}}$$

In order to study the invariant measure  $\mu$ , we apply the theory of semimartingale reflected Brownian motions developed by **M. Harrison, M. Reiman, R. Williams** and others.

In addition to the model assumptions, we assume **linearly growing variances**:

$$\sigma_2^2 - \sigma_1^2 = \sigma_3^2 - \sigma_2^2 = \cdots = \sigma_n^2 - \sigma_{n-1}^2.$$

## Invariant distribution of gaps and index

Let us define the indicator map  $\mathbb{R}^n \ni x \mapsto \mathbf{p}^x \in \Sigma_n$  such that  $x_{\mathbf{p}^x(1)} \geq x_{\mathbf{p}^x(2)} \geq \cdots \geq x_{\mathbf{p}^x(n)}$ , and the **index process**  $\mathfrak{P}_t := \mathbf{p}^{Y(t)}$ .

**Proposition** Under the **stability** and the **linearly growing variance** conditions the invariant distribution  $\nu(\cdot)$  of  $(\Xi(\cdot), \mathfrak{P}_\cdot)$  is

$$\nu(A \times B) = \left( \sum_{\mathbf{q} \in \Sigma_n} \prod_{k=1}^{n-1} \lambda_{\mathbf{q}, k}^{-1} \right)^{-1} \sum_{\mathbf{p} \in \Sigma_n} \int_A \exp(-\langle \lambda_{\mathbf{p}}, z \rangle) dz$$

for every measurable set  $A \times B$  where  $\lambda_{\mathbf{p}} := (\lambda_{\mathbf{p}, 1}, \dots, \lambda_{\mathbf{p}, n-1})'$  is the vector of components

$$\lambda_{\mathbf{p}, k} := \frac{-4(\sum_{\ell=1}^k g_\ell + \gamma_{\mathbf{p}(\ell)})}{\sigma_k^2 + \sigma_{k+1}^2} > 0 ; \quad \mathbf{p} \in \Sigma_n, \quad 1 \leq k \leq n-1.$$

Proof: an extension from M. Harrison and R. Williams ('87).

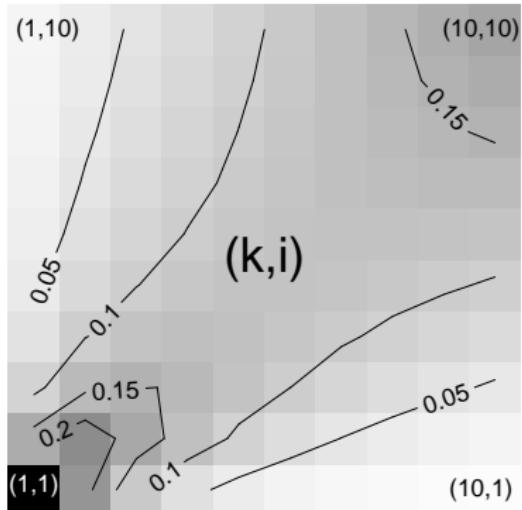
# Average occupation time

**Corollary** The average occupation times are

$$\theta_{\mathbf{p}} = \left( \sum_{\mathbf{q} \in \Sigma_n} \prod_{k=1}^{n-1} \lambda_{\mathbf{q}, k}^{-1} \right)^{-1} \prod_{j=1}^{n-1} \lambda_{\mathbf{p}, j}^{-1} \quad \text{and} \quad \theta_{k,i} = \sum_{\{\mathbf{p} \in \Sigma_n : \mathbf{p}(k) = i\}} \theta_{\mathbf{p}}$$

for  $\mathbf{p} \in \Sigma_n$  and  $1 \leq k, i \leq n$ .

- If all  $\gamma_i = 0$  and  $\sigma_1^2 = \dots = \sigma_n^2$ , then  $\theta_{k,i} = \frac{1}{n}$  for  $1 \leq k, i \leq n$ .
- Heat map of  $\theta_{k,i}$  when  $n = 10$ ,  $\sigma_k^2 = 1 + k$ ,  $g_k = -1$  for  $k = 1, \dots, 9$ ,  $g_{10} = 9$ , and  $\gamma_i = 1 - (2i)/(n+1)$  for  $i = 1, \dots, n$ .



## Market weights come from Pareto type

**Corollary** The joint invariant distribution of market shares

$$\mu_{(i)}(\cdot) := X_{(i)}(\cdot)/(X_1(\cdot) + \cdots + X_n(\cdot)); \quad i = 1, \dots, n$$

has the density

$$\wp(m_1, \dots, m_{n-1})$$

$$= \sum_{\mathbf{p} \in \Pi_n} \theta_{\mathbf{p}} \frac{\lambda_{\mathbf{p},1} \cdots \lambda_{\mathbf{p},n-1}}{m_1^{\lambda_{\mathbf{p},1}+1} \cdot m_2^{\lambda_{\mathbf{p},2}-\lambda_{\mathbf{p},1}+1} \cdots m_{n-1}^{\lambda_{\mathbf{p},n-1}-\lambda_{\mathbf{p},n-2}+1} m_n^{-\lambda_{\mathbf{p},n-1}+1}},$$

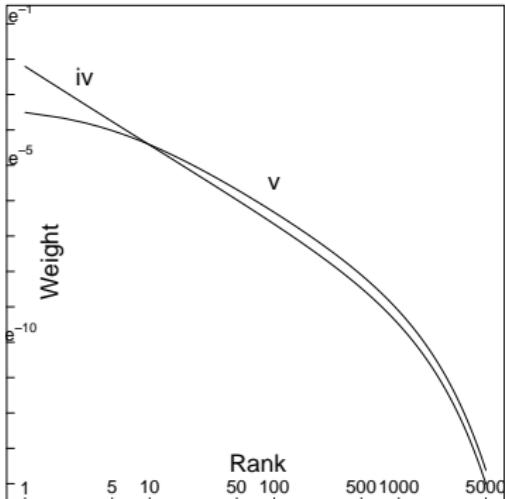
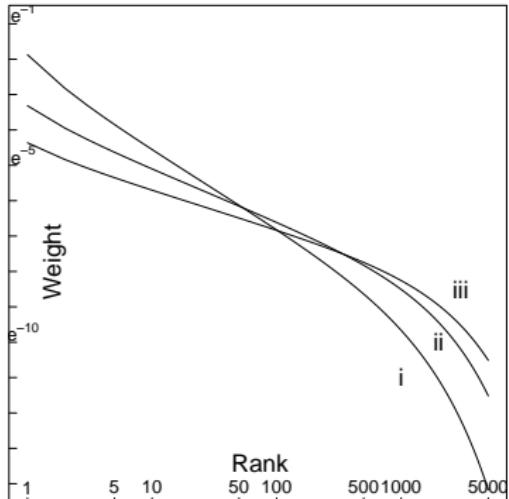
$$0 < m_n \leq m_{n-1} \leq \dots \leq m_1 < 1,$$

$$m_n = 1 - m_1 - \cdots - m_{n-1}.$$

This is a distribution of ratios of **Pareto** type distribution.

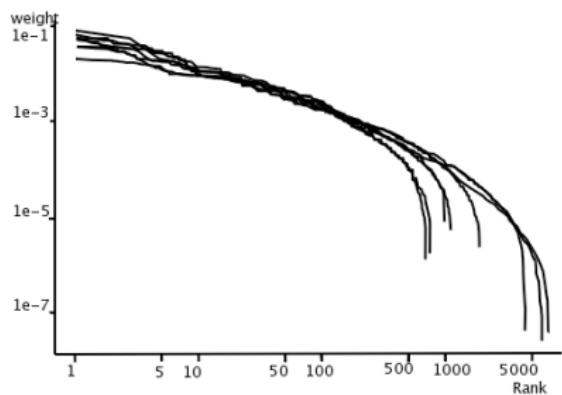
# Expected capital distribution curves

From the expected slopes  $\mathbb{E}^\nu \left[ \frac{\log \mu_{(k)} - \log \mu_{(k-1)}}{\log(k+1) - \log k} \right] = -\frac{\mathbb{E}^\nu(\Xi_k)}{\log(1+k^{-1})}$  we obtain expected capital distribution curves.



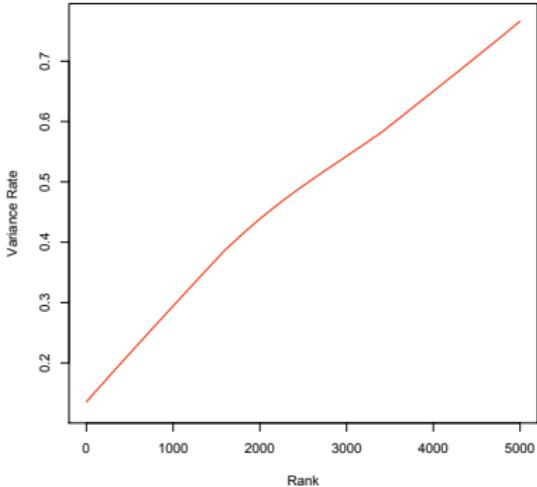
- ▶  $n = 5000, g_n = c_*(2n - 1), g_k = 0, 1 \leq k \leq n - 1, \gamma_1 = -c_*, \gamma_i = -2c_*, 2 \leq i \leq n, \sigma_k^2 = 0.075 + 6k \times 10^{-5}, 1 \leq k \leq n.$  (i)  $c_* = 0.02$ , (ii)  $c_* = 0.03$ , (iii)  $c_* = 0.04$ .
- ▶ (iv)  $c_* = 0.02, g_1 = -0.016, g_k = 0, 2 \leq k \leq n - 1, g_n = (0.02)(2n - 1) + 0.016,$
- ▶ (v)  $g_1 = \dots = g_{50} = -0.016, g_k = 0, 51 \leq k \leq n - 1, g_n = (0.02)(2n - 1) + 0.8.$

# Empirical data



Historical capital distribution curves. Data 1929-1999.

Source: Fernholz ('02)



Growing variances. 1990-1999.

# Capital Stocks and Portfolio Rules

- Market  $X = ((X_1(t), \dots, X_n(t)), t \geq 0)$  of  $n$  companies

$$\log \frac{X_i(T)}{X_i(0)} = \int_0^T \textcolor{red}{G}_i(t) dt + \int_0^T \sum_{\nu=1}^n \textcolor{blue}{S}_{i,\nu}(t) dW_\nu(t),$$

with initial capital  $X_i(0) = x_i > 0$ ,  $i = 1, \dots, n$ ,  $0 \leq T < \infty$ .

Define  $a_{ij}(\cdot) = \sum_{\nu=1}^n S_{i\nu}(\cdot) S_{j\nu}(\cdot)$  and  $A_{ij}(\cdot) = \int_0^\cdot a_{ij}(t) dt$ .

- Long only Portfolio rule  $\pi$  and its wealth  $V^\pi$ .

Choose  $\pi \in \Delta_+^n := \{x \in \mathbb{R}^n : \sum x_i = 1, x_i \geq 0\}$

invest  $\pi_i V^\pi$  of money to company  $i$  for  $i = 1, \dots, n$ , i.e.,  
 $\pi_i V^\pi / X_i$  share of company  $i$ :

$$dV^\pi(t) = \sum_{i=1}^n \frac{\pi_i(t) V^\pi(t)}{X_i(t)} dX_i(t), \quad 0 \leq t < \infty,$$

$$V^\pi(0) = w.$$

# Capital Stocks and Portfolio Rules

- Market  $X = ((X_1(t), \dots, X_n(t)), t \geq 0)$  of  $n$  companies

$$\log \frac{X_i(T)}{X_i(0)} = \int_0^T \textcolor{red}{G}_i(t) dt + \int_0^T \sum_{\nu=1}^n \textcolor{blue}{S}_{i,\nu}(t) dW_\nu(t),$$

with initial capital  $X_i(0) = x_i > 0$ ,  $i = 1, \dots, n$ ,  $0 \leq T < \infty$ .

Define  $a_{ij}(\cdot) = \sum_{\nu=1}^n S_{i\nu}(\cdot) S_{j\nu}(\cdot)$  and  $A_{ij}(\cdot) = \int_0^\cdot a_{ij}(t) dt$ .

- Long only Portfolio rule  $\pi$  and its wealth  $V^\pi$ .

Choose  $\pi \in \Delta_+^n := \{x \in \mathbb{R}^n : \sum x_i = 1, \textcolor{blue}{x}_i \geq 0\}$

invest  $\pi_i V^\pi$  of money to company  $i$  for  $i = 1, \dots, n$ , i.e.,

$\pi_i V^\pi / X_i$  share of company  $i$ :

$$dV^\pi(t) = \sum_{i=1}^n \frac{\pi_i(t) V^\pi(t)}{X_i(t)} dX_i(t), \quad 0 \leq t < \infty,$$

$$V^\pi(0) = w.$$

# Capital Stocks and Portfolio Rules

- Market  $X = ((X_1(t), \dots, X_n(t)), t \geq 0)$  of  $n$  companies

$$\log \frac{X_i(T)}{X_i(0)} = \int_0^T \textcolor{red}{G}_i(t) dt + \int_0^T \sum_{\nu=1}^n \textcolor{blue}{S}_{i,\nu}(t) dW_\nu(t),$$

with initial capital  $X_i(0) = x_i > 0$ ,  $i = 1, \dots, n$ ,  $0 \leq T < \infty$ .

Define  $a_{ij}(\cdot) = \sum_{\nu=1}^n S_{i\nu}(\cdot) S_{j\nu}(\cdot)$  and  $A_{ij}(\cdot) = \int_0^\cdot a_{ij}(t) dt$ .

- Long only Portfolio rule  $\pi$  and its wealth  $V^\pi$ .

Choose  $\pi \in \Delta_+^n := \{x \in \mathbb{R}^n : \sum x_i = 1, \textcolor{blue}{x}_i \geq 0\}$

invest  $\pi_i V^\pi$  of money to company  $i$  for  $i = 1, \dots, n$ , i.e.,

$\pi_i V^\pi / X_i$  share of company  $i$ :

$$dV^\pi(t) = \sum_{i=1}^n \frac{\pi_i(t) V^\pi(t)}{X_i(t)} dX_i(t), \quad 0 \leq t < \infty,$$

$$V^\pi(0) = w.$$

# Portfolios and Relative Arbitrage

- Market portfolio: Take

$\pi(t) = \mathbf{m}(t) = (\mathbf{m}_1(t), \dots, \mathbf{m}_n(t)) \in \Delta_+^n$  where

$$\mathbf{m}_i(t) = \frac{X_i(t)}{X_1 + \dots + X_n(t)}, \quad i = 1, \dots, n, \quad 0 \leq t < \infty.$$

- Diversity weighted portfolio: Given  $p \in [0, 1]$ , take  
 $\pi_i(t) = \frac{(\mathbf{m}_i(t))^p}{\sum_{j=1}^n (\mathbf{m}_j(t))^p}$  for  $i = 1, \dots, n$ ,  $0 \leq t < \infty$ .
- Functionally generated portfolio (Fernholz ('02) & Karatzas ('08)).
- A portfolio  $\pi$  represents an arbitrage opportunity relative to another portfolio  $\rho$  on  $[0, T]$ , if

$$\mathbb{P}(V^\pi(T) \geq V^\rho(T)) = 1, \quad \mathbb{P}(V^\pi(T) > V^\rho(T)) > 0.$$

*Can we find an arbitrage opportunity  $\pi$  relative to  $\mathbf{m}$  ?*

# Portfolios and Relative Arbitrage

- Market portfolio: Take

$$\pi(t) = \mathbf{m}(t) = (\mathbf{m}_1(t), \dots, \mathbf{m}_n(t)) \in \Delta_+^n \text{ where}$$

$$\mathbf{m}_i(t) = \frac{X_i(t)}{X_1 + \dots + X_n(t)}, \quad i = 1, \dots, n, \quad 0 \leq t < \infty.$$

- Diversity weighted portfolio: Given  $p \in [0, 1]$ , take  
 $\pi_i(t) = \frac{(\mathbf{m}_i(t))^p}{\sum_{j=1}^n (\mathbf{m}_j(t))^p}$  for  $i = 1, \dots, n$ ,  $0 \leq t < \infty$ .
- Functionally generated portfolio (Fernholz ('02) & Karatzas ('08)).
- A portfolio  $\pi$  represents an arbitrage opportunity relative to another portfolio  $\rho$  on  $[0, T]$ , if

$$\mathbb{P}(V^\pi(T) \geq V^\rho(T)) = 1, \quad \mathbb{P}(V^\pi(T) > V^\rho(T)) > 0.$$

Can we find an arbitrage opportunity  $\pi$  relative to  $\mathbf{m}$  ?

## Constant-portfolio

For a constant-proportion  $\pi(\cdot) \equiv \pi$ ,

$$V^\pi(t) = w \cdot \exp \left[ \sum_{i=1}^n \pi_i \cdot \left\{ \frac{A_{ii}(t)}{2} + \log \left( \frac{X_i(t)}{X_i(0)} \right) \right\} - \frac{1}{2} \sum_{i,j=1}^n \pi_i A_{ij}(t) \pi_j \right]$$

for  $0 \leq t < \infty$ .

Here  $A_{ij}(\cdot) = \int_0^\cdot a_{ij}(t) dt$  and  $a_{ij}(\cdot) = \sum_{\nu=1}^n S_{i\nu}(\cdot) S_{j\nu}(\cdot)$ ,

$$d Y(t) = \textcolor{red}{G}(Y(t))dt + \textcolor{blue}{S}(Y(t))dW(t); \quad 0 \leq t < \infty,$$

$$\begin{aligned} \textcolor{red}{G}(y) &= \sum_{\mathbf{p} \in \Sigma_n} (g_{\mathbf{p}^{-1}(1)} + \gamma_1 + \gamma, \dots, g_{\mathbf{p}^{-1}(n)} + \gamma_n + \gamma)' \cdot \mathbf{1}_{\mathcal{R}_{\mathbf{p}}}(y), \\ \textcolor{blue}{S}(y) &= \sum_{\mathbf{p} \in \Sigma_n} \underbrace{\text{diag}(\sigma_{\mathbf{p}^{-1}(1)}, \dots, \sigma_{\mathbf{p}^{-1}(n)})}_{\mathfrak{s}_{\mathbf{p}}} \cdot \mathbf{1}_{\mathcal{R}_{\mathbf{p}}}(y); \quad y \in \mathbb{R}^n. \end{aligned}$$

## Target Portfolio(Cover('91) & Jamshidian('92))

$$V^\pi(\cdot) = w \cdot \exp \left[ \sum_{i=1}^n \pi_i \left\{ \frac{A_{ii}(t)}{2} + \log \left( \frac{X_i(\cdot)}{X_i(0)} \right) \right\} - \frac{1}{2} \sum_{i,j=1}^n \pi_i A_{ij}(\cdot) \pi_j \right]$$

Target Portfolio  $\Pi^*(t)$  maximizes the wealth  $V^\pi(t)$  for  $t \geq 0$ :

$$V_*(t) := \max_{\pi \in \Delta_+^n} V^\pi(t), \quad \Pi^*(t) := \arg \max_{\pi \in \Delta_+^n} V^\pi(t),$$

where by Lagrange method we obtain

$$\begin{aligned} \Pi_i^*(t) &= \left( 2A_{ii}(t) \sum_{j=1}^n \frac{1}{A_{jj}(t)} \right)^{-1} \left[ 2 - n - 2 \sum_{j=1}^n \frac{1}{A_{jj}(t)} \log \left( \frac{X_j(t)}{X_j(0)} \right) \right] \\ &\quad + \frac{1}{2} + \frac{1}{A_{ii}(t)} \log \left( \frac{X_i(t)}{X_i(0)} \right); \quad 0 \leq t < \infty. \end{aligned}$$

# Asymptotic Target Portfolio

Under the hybrid Atlas model with the assumptions

$$v(\pi) := \lim_{T \rightarrow \infty} \frac{1}{T} \log V^\pi(T) = \gamma + \underbrace{\frac{1}{2} \left( \sum_{i=1}^n \pi_i \alpha_{ii}^\infty - \sum_{i=1}^n \pi_i \alpha_{ii}^\infty \pi_j \right)}_{\gamma_\pi^\infty}$$

where  $(\alpha_{ij}^\infty)_{1 \leq i, j \leq n}$  is the (i,i) element of

$$\alpha^\infty := \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T (a_{ij}(t))_{1 \leq i, j \leq n} dt = \sum_{\mathbf{p} \in \Sigma_n} \theta_{\mathbf{p}} \xi_{\mathbf{p}} \xi'_{\mathbf{p}}.$$

Asymptotic target portfolio maximizes the excess growth  $\gamma_\pi^\infty$ :

$$\bar{\pi} := \arg \max_{\pi \in \Delta_+^n} \left( \sum_{i=1}^n \pi_i \alpha_{ii}^\infty - \sum_{i=1}^n \pi_i \alpha_{ii}^\infty \pi_j \right).$$

We obtain

$$\bar{\pi}_i = \frac{1}{2} \left[ 1 - \frac{n-2}{\alpha_{ii}^\infty} \left( \sum_{j=1}^n \frac{1}{\alpha_{jj}^\infty} \right)^{-1} \right] = \lim_{t \rightarrow \infty} \Pi_j^*(t); \quad i = 1, \dots, n.$$

# Asymptotic Target Portfolio

Under the hybrid Atlas model with the assumptions

$$v(\pi) := \lim_{T \rightarrow \infty} \frac{1}{T} \log V^\pi(T) = \gamma + \underbrace{\frac{1}{2} \left( \sum_{i=1}^n \pi_i \alpha_{ii}^\infty - \sum_{i=1}^n \pi_i \alpha_{ii}^\infty \pi_j \right)}_{\gamma_\pi^\infty}$$

where  $(\alpha_{ij}^\infty)_{1 \leq i, j \leq n}$  is the (i,i) element of

$$\alpha^\infty := \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T (a_{ij}(t))_{1 \leq i, j \leq n} dt = \sum_{\mathbf{p} \in \Sigma_n} \theta_{\mathbf{p}} \xi_{\mathbf{p}} \xi'_{\mathbf{p}}.$$

Asymptotic target portfolio maximizes the excess growth  $\gamma_\pi^\infty$ :

$$\bar{\pi} := \arg \max_{\pi \in \Delta_+^n} \left( \sum_{i=1}^n \pi_i \alpha_{ii}^\infty - \sum_{i=1}^n \pi_i \alpha_{ii}^\infty \pi_j \right).$$

We obtain

$$\bar{\pi}_i = \frac{1}{2} \left[ 1 - \frac{n-2}{\alpha_{ii}^\infty} \left( \sum_{j=1}^n \frac{1}{\alpha_{jj}^\infty} \right)^{-1} \right] = \lim_{t \rightarrow \infty} \Pi_i^*(t); \quad i = 1, \dots, n.$$

## Universal Portfolio(Cover('91) & Jamshidian('92))

Universal portfolio is defined as

$$\hat{\Pi}_i(\cdot) := \frac{\int_{\Delta_+^n} \pi_i V^\pi(\cdot) d\pi}{\int_{\Delta_+^n} V^\pi(\cdot) d\pi}, \quad 1 \leq i \leq n, \quad V^{\hat{\Pi}}(\cdot) = \frac{\int_{\Delta_+^n} V^\pi(\cdot) d\pi}{\int_{\Delta_+^n} d\pi}.$$

Proposition Under the hybrid Atlas model with the model assumptions,

$$\lim_{T \rightarrow \infty} \frac{1}{T} \log \frac{V^{\hat{\Pi}}(T)}{V^{\bar{\pi}}(T)} = \lim_{T \rightarrow \infty} \frac{1}{T} \log \frac{V^{\hat{\Pi}}(T)}{V_*(T)} = 0 \quad \mathbb{P}-a.s.$$

## Universal Portfolio(Cover('91) & Jamshidian('92))

Universal portfolio is defined as

$$\hat{\Pi}_i(\cdot) := \frac{\int_{\Delta_+^n} \pi_i V^\pi(\cdot) d\pi}{\int_{\Delta_+^n} V^\pi(\cdot) d\pi}, \quad 1 \leq i \leq n, \quad V^{\hat{\Pi}}(\cdot) = \frac{\int_{\Delta_+^n} V^\pi(\cdot) d\pi}{\int_{\Delta_+^n} d\pi}.$$

**Proposition** Under the hybrid Atlas model with the model assumptions,

$$\lim_{T \rightarrow \infty} \frac{1}{T} \log \frac{V^{\hat{\Pi}}(T)}{V^{\bar{\pi}}(T)} = \lim_{T \rightarrow \infty} \frac{1}{T} \log \frac{V^{\hat{\Pi}}(T)}{V_*(T)} = 0 \quad \mathbb{P} - a.s.$$

# Conclusion

- ▶ Ergodic properties of Hybrid Atlas model
- ▶ Diversity weighted portfolio, Target portfolio, Universal portfolio.
- ▶ Further topics: short term arbitrage, generalized portfolio generating function, large market ( $n \rightarrow \infty$ ), numéraire portfolio, data implementation.

## References:

1. arXiv: 0909.0065
2. arXiv: 0810.2149 (to appear in Annals of Applied Probability)

Tomoyuki Ichiba (UCSB)  
ichiba@pstat.ucsb.edu