

The distribution of Brownian and Bessel quantiles.

(A)/

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Let $(B_t, t \geq 0)$ be a 1-dimensional Brownian motion starting from 0.

The computation of the price of Asian options amounts to the computation of the following quantity:

$$(0.a) \quad C_T^\gamma(k) \stackrel{\text{def}}{=} E\left[\left(\frac{1}{T} \int_0^T \exp(B_s + \gamma s) - k\right)^+\right],$$

for some given time T , and some reals γ and k . A number of results have been obtained about this topic (see H. Geman-M. Yor [1], [2], and [3], [4], in particular).

In November 1993, P. Embrechts suggested that, instead of considering, as in (0.a), the time-average of $\exp(B_s + \gamma s)$ on the interval $[0, T]$, it would be interesting to study the median of this (random) function of s ($\leq T$), and, more generally, the α -quantiles, for every $0 < \alpha < 1$. Precisely, to simplify the discussion, we may take, without loss of generality, $T = 1$, and we define, for $0 \leq \alpha < 1$:

$$X_\alpha^{(\gamma)} = \inf_{\alpha} \left\{ \alpha : \int_0^1 du \frac{1}{u} (\exp(B_u + \gamma u) \leq x) > \alpha \right\}.$$

The main aim of this paper is to find the law of

$X_\alpha^{(\gamma)}$ explicitly, and to compute:

$$(0.b) \quad M_\alpha^\gamma(x, k) \stackrel{\text{def}}{=} E\left[(X_\alpha^{(\gamma)} - k)^+\right].$$

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Secton 1 is devoted to this problem in the case $\beta=0$, for which the formulae²⁾ are most applicat, whereas in secton 2, the general case, with $\beta \in \mathbb{R}$, is studied.

In Secton 3, two variants of the preceding question are studied; the first variant concuns the study of the Brownian quantiles when the probability space $([0,1]; dt)$ is being replaced by $([0,\infty[; e^{-t} dt)$; thus, one is interested in:

$$Y_{\alpha}^{(1)} = \inf \left\{ x : \int_0^{\infty} dt e^{-t} \mathbf{1}_{(Bt + \beta t \leq x)} > \alpha \right\};$$

the second variant concuns the Brownian quantiles over the probability space $([0,T_1]; \frac{dt}{T_1})$, where $T_1 = \inf \{ t : Bt + \beta t = 1 \}$; hence, one is interested in:

$$Z_{\alpha}^{(1)} = \inf \left\{ x : \frac{1}{T_1} \int_0^{T_1} dt \mathbf{1}_{(Bt + \beta t \leq x)} > \alpha \right\}.$$

Finally, in Secton 4, slightly different quantities are considered,

namely:

$$\eta(\delta) = \inf_{\alpha} \left\{ x : \int_0^{\infty} dt \mathbf{1}_{(R_t \leq x)} > \alpha \right\},$$

and

$$\mu_{\alpha}^{(\delta)} = \inf \left\{ x : \int_0^{\infty} dt \mathbf{1}_{(|Bt| + \frac{\beta}{\delta} t \leq x)} > \alpha \right\}.$$

2. The general case: \mathbb{R} real.

Keeping with the notation in the introduction we consider here:

$$X_\alpha^{(1)} = \inf \left\{ u : \int_0^1 du \mathbf{1}_{(B_u^{(1)} \leq x)} > \alpha \right\},$$

where $B_u^{(1)} = B_u + \sqrt{u}$, $u \geq 0$.

The symmetry relation (1.c) may be extended as follows:

$$(2.a) \quad X_\alpha^{(1)} \stackrel{\text{(law)}}{=} -X_{-\alpha}^{(-1)}.$$

Hence, to derive the distribution of $X_\alpha^{(1)}$, it suffices to compute $P(X_\alpha^{(1)} > x)$,

for every α and $x \geq 0$.

With obvious notation, we remark, following the arguments developed in Section 1,

that:

$$\begin{aligned} (X_\alpha^{(1)} > x) &= \left(T_x^{(1)} + \int_{T_x^{(1)}}^1 dt \mathbf{1}_{(B_t^{(1)} < x)} < \alpha \right) \\ &\stackrel{\text{(law)}}{=} \left(T_x^{(1)} + \int_0^{1-T_x^{(1)}} dt \mathbf{1}_{(B_t^{(1)} < 0)} < \alpha \right). \end{aligned}$$

Hence, we obtain:

$$(2.b) \quad P(X_\alpha^{(1)} > x) = \int_0^\alpha dt \theta_x^{(1)}(t) P\left(\int_0^{1-t} du \mathbf{1}_{(B_u^{(1)} < 0)} < \alpha - t\right),$$

where:

$$\begin{aligned} \theta_x^{(1)}(t) dt &= P(T_x^{(1)} \in dt) = E\left[T_x^{(1)} e^{dt}; \exp\left(\sqrt{x} - \frac{\sqrt{t}}{2}\right)\right] \\ &= \frac{dt}{\sqrt{2T_x^{(1)} + 3}} \exp\left(-\frac{x^2}{2t} + \sqrt{x} - \frac{\sqrt{t}}{2}\right) \end{aligned}$$

3. Two Variants

The purpose of this section is to show how the arguments developed in Sections 1 and 2, although elementary, may yield results in somewhat different contexts.

(3.1) As a first variant, we shall consider:

$$Y_\alpha = \inf \left\{ x : \int_0^\infty dt e^{-t} 1_{(B_t < x)} > \alpha \right\} \quad (0 < \alpha < 1)$$

With the same notation as in (1.2) above, we find, for $x > 0$:

$$\begin{aligned} (Y_\alpha > x) &= \left(\int_0^{T_x} dt e^{-t} + \int_{T_x}^\infty e^{-t} 1_{(B_t < x)} dt < \alpha \right) \\ &= \left(\int_0^{T_x} dt e^{-t} + e^{-T_x} A < \alpha \right), \end{aligned}$$

where $A = \int_0^\infty du e^{-u} 1_{(B_u < 0)}$.

Hence, we obtain: $(Y_\alpha > x) = (T_x < \log(\frac{1-A}{1-\alpha}))$

$$\stackrel{\text{(law)}}{=} \left(\frac{x}{|N|} < (\log(\frac{1-A}{1-\alpha}))^{1/2} \right).$$

Similar arguments yield, for $x < 0$:

$$(Y_\alpha > x) \stackrel{\text{(law)}}{=} \left(\frac{-x}{|N|} > (\log \frac{A}{\alpha})^{1/2} \right).$$

Consequently, we have obtained the following
Proposition: Let $0 < \alpha < 1$. The distribution of Y_α is characterized by:

$$P(Y_\alpha < x) = \begin{cases} \sqrt{\frac{2}{\pi}} E \left[\frac{1}{(\lambda_+)^{1/2}} \exp \left(-\frac{x^2}{2\lambda_+} \right) \right] & (x > 0) \\ \sqrt{\frac{2}{\pi}} E \left[\frac{1}{(\lambda_-)^{1/2}} \exp \left(-\frac{x^2}{2\lambda_-} \right) \right] & (x < 0) \end{cases},$$

where: $\lambda_+ = \log \left(\frac{1-A}{1-\alpha} \right)$, $\lambda_- = \log \left(\frac{A}{\alpha} \right)$, and $A = \int_0^\infty dt e^{-t} 1_{(B_t < 0)}$

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1)

The distribution of Brownian quantiles.

November 16th

Let (B_t) be a 1-dimensional Brownian motion starting from 0.

Define, for $0 < \alpha < 1$:

$$X_\alpha = \inf \left\{ u : \int_0^1 ds \mathbb{1}_{(B_s < u)} = \alpha \right\}.$$

I will show the following formula:

$$P(X_\alpha \in dx) = \begin{cases} \frac{\sqrt{2}}{\pi} E \left[g \leq \alpha ; \sqrt{\frac{1-g}{\alpha-g}} \exp -\frac{x^2}{2} \left(\frac{1-g}{\alpha-g} \right) \right] & (x \geq 0) \\ \frac{\sqrt{2}}{\pi} E \left[g \geq \alpha ; \frac{1}{\sqrt{1-\frac{\alpha}{g}}} \exp \left(-\frac{x^2}{2(1-\frac{\alpha}{g})} \right) \right] & (x \leq 0) \end{cases}$$

where g is arc sine distributed.

Proof:

I will use the following identity:

$$(X_\alpha > x) = \left(\int_0^1 ds \mathbb{1}_{(B_s < x)} < \alpha \right).$$

(i) Assume $x > 0$; define $T_x = \inf \{u : B_u = x\}$.

$$\text{Then, we have: } P(X_\alpha > x) = P \left(T_x + \int_{T_x}^1 ds \mathbb{1}_{(B_s < x)} < \alpha ; T_x < 1 \right)$$

Since $(B_{T_x+u} - x ; u \geq 0)$ is a Brownian motion independent of \mathcal{F}_{T_x} , we have:

$$P(X_\alpha > x) = P(T_x + (1-T_x)g < \alpha ; T_x < 1),$$

where g is arc sine distributed, and independent of T_x .

2)

Therefore, we have:

$$\begin{aligned}
 P(X_\alpha > \alpha) &= P(T_\alpha(1-q) + q < \alpha; T_\alpha < 1) \\
 &= P(q < \alpha; \alpha^2(1-q) < N^2; \alpha^2 < N^2) \\
 &= P(q < \alpha; \alpha \leq \sqrt{\frac{\alpha-q}{1-q}} |N|). \\
 &= \sqrt{\frac{2}{\pi}} E \left[q < \alpha; \sqrt{\frac{1-q}{\alpha-q}} \int_x^\infty d\beta \exp \left(-\frac{\beta^2}{2} \left(\frac{1-q}{\alpha-q} \right) \right) \right].
 \end{aligned}$$

It now remains to differentiate with respect to α to obtain the formula for $\alpha > 0$.

(ii) Assume $\alpha < 0$.

Again, when I consider: $\left(\int_0^1 ds 1_{(B_s \leq x)} \leq \alpha \right)$,

I have to decompose with $(T_\alpha \leq 1)$, and $(T_\alpha > 1)$.

On $T_\alpha > 1$, we have:

$$\int_0^1 ds 1_{(B_s \leq x)} = 0 \cdot (< \alpha)$$

Therefore, we obtain:

$$\begin{aligned}
 P(X_\alpha > \alpha) &= P(T_\alpha > 1) + P(T_\alpha \leq 1; \int_{T_\alpha}^1 ds 1_{(B_s \leq x)} \leq \alpha) \\
 &= P(T_\alpha > 1) + P(T_\alpha \leq 1; (1-T_\alpha)q \leq \alpha) \\
 &= P(|N| \leq |\alpha|) + P(q \leq \alpha) P(|\alpha| \leq |N|) + E \left[q \geq \alpha; 1 - \frac{\alpha}{q} \leq \frac{\alpha^2}{N^2} \leq 1 \right]
 \end{aligned}$$

3)

Therefore, writing $g = -x$, we get:

$$\begin{aligned} P(X_\alpha > x) &= \sqrt{\frac{2}{\pi}} \int_0^g dy e^{-y^2/2} + P(g \leq \alpha) \sqrt{\frac{2}{\pi}} \int_g^\infty dy e^{-y^2/2} \\ &\quad + E[(g > \alpha) \sqrt{\frac{2}{\pi}} \int_g^{\frac{-x}{g}} dy \exp(-\frac{y^2}{2})]. \end{aligned}$$

Then, taking the derivative with respect to x on both sides, we get that the density, for $x < 0$, is:

$$\sqrt{\frac{2}{\pi}} E\left[g > \alpha; \frac{1}{\sqrt{1-\frac{x}{g}}} \exp\left(-\frac{x^2}{2(1-\frac{x}{g})}\right)\right], \text{ which is the}$$

second formula \square .

Further simplifications: 1) Using the explicit distribution of g , we obtain the

following formula:

$$P(X_\alpha \in dx) = \begin{cases} \sqrt{\frac{2}{\pi}} E\left[\exp - \frac{x^2}{2} \left(1 + \left(\frac{1-\alpha}{\alpha}\right) \frac{1}{g}\right)\right] & (x \geq 0) \\ \sqrt{\frac{2}{\pi}} E\left[\exp - \frac{x^2}{2} \left(1 + \left(\frac{\alpha}{1-\alpha}\right) \frac{1}{g}\right)\right] & (x \leq 0) \end{cases}$$

It appears clearly with this formula that:

$-X_\alpha \stackrel{\text{(law)}}{=} X_{(1-\alpha)}$, as can be shown directly from the symmetry of BM.

2) The preceding formula may be simplified again;
we introduce the following notation:

$$\frac{1-\alpha}{\alpha} = \beta^2 \quad (\beta > 0).$$

We will use the following

Lemma:

$$E \left[\exp \left(-\frac{y^2}{2} \left(\frac{1}{\beta} \right) \right) \right] = \Phi(|y|),$$

where,

$$\Phi(z) = \sqrt{\frac{2}{\pi}} \int_z^\infty dx \exp \left(-\frac{x^2}{2} \right) = P(|N| > z).$$

Proof: We know that: $\frac{1}{\beta} \stackrel{\text{(law)}}{=} 1 + C^2$, where C is a standard

Cauchy variable. Then, we have:

$$\begin{aligned} E \left[\exp \left(-\frac{y^2}{2} \left(\frac{1}{\beta} \right) \right) \right] &= E \left[\exp \left(-\frac{y^2}{2} (1+C^2) \right) \right] \\ &= \exp \left(-\frac{y^2}{2} \right) E \left[\exp (iyNC) \right] \\ &= \exp \left(-\frac{y^2}{2} \right) E \left[\exp (-|y||N|) \right]. \\ &= \sqrt{\frac{2}{\pi}} \int_0^\infty dx \exp \left(-\frac{(x+|y|)^2}{2} \right) = \Phi(|y|) \end{aligned}$$

Now, we can write:

$$P(X_\alpha \in dx) = \begin{cases} \sqrt{\frac{2}{\pi}} \exp \left(-\frac{x^2}{2} \right) \Phi(\beta x) dx, & x > 0. \\ \sqrt{\frac{2}{\pi}} \exp \left(-\frac{x^2}{2} \right) \Phi \left(\frac{|x|}{\beta} \right) dx, & x \leq 0. \end{cases}$$

5)

In the particular case where $\alpha = \frac{1}{2}$, we get: $\beta = 1$, and then the previous formula becomes:

$$\mathbb{P}\left(X_{\frac{1}{2}} \in dx\right) = \sqrt{\frac{2}{\pi}} \left(\exp\left(-\frac{x^2}{2}\right)\right) \Phi(|x|) dx, \quad (x \in \mathbb{R}).$$

Thus, we have:

$$\mathbb{P}\left(|X_{\frac{1}{2}}| \geq y\right) = (\Phi(y))^2,$$

which proves that: $|X_{\frac{1}{2}}| \stackrel{(law)}{=} \inf(|N|, |N'|)$.

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On the "true" Brownian quantiles

November, 16th, 1993

Let $(B_t, t \geq 0)$ be a 1-dimensional Brownian motion starting from 0.

For any fixed t , define, for $0 < \alpha < t$:

$$(1) \quad X_\alpha(t) = \inf \left\{ x : \int_0^t \mathrm{d}u \mathbf{1}_{(B_u \leq x)} = \alpha \right\}$$

We are interested in finding the distribution of $X_\alpha(1)$, for a given $\alpha < 1$.

We will take advantage of the scaling property of Brownian motion, from which we get:

$$(2) \quad X_\alpha(t) = \sqrt{t} X_{\frac{\alpha}{t}}(1)$$

Again, I keep t fixed. Since: $\alpha \mapsto X_\alpha(t)$, $\alpha \leq t$, is the inverse of the increasing process:

$$x \mapsto \int_0^t \mathrm{d}u \mathbf{1}_{(B_u \leq x)} = \int_{-\infty}^x \mathrm{d}y \frac{e^y}{t},$$

we have, for any $f: \mathbb{R} \rightarrow \mathbb{R}_+$:

$$(3) \quad \begin{aligned} & \int_{-\infty}^{\infty} dx \frac{e^x}{t} \exp \left(-\lambda \int_{-\infty}^x \mathrm{d}y \frac{e^y}{t} \right) f(x) \\ &= \int_0^t dx \exp(-\lambda x) f(X_\alpha(t)) \stackrel{(\text{law})}{=} t \int_0^1 d\beta \exp(-\lambda \beta t) f(\sqrt{t} X_\beta(1)) \end{aligned}$$

Moreover, if we assume f to have compact support, we get, by integration by parts, that (3) is equal to:

$$\frac{1}{\lambda} \int_{-\infty}^{\infty} dx \exp \left(-\lambda \int_{-\infty}^x \mathrm{d}y \frac{e^y}{t} \right) f'(x).$$

Hence, this is equal, in law, to:

$$t \int_0^1 d\beta \exp(-\lambda \beta t) f(\sqrt{t} X_\beta(1)).$$

Now, the distribution of $(l_t^y; y \in \mathbb{R})$ is not so easy to manipulate - therefore, we randomize the time t , i.e.: we replace t by T_θ , an exponential random variable with parameter θ ; thus, we get:

$$\begin{aligned} (4) \quad & E \left[T \int_0^1 d\beta \exp(-\lambda \beta T) f(\sqrt{T} X_\beta(1)) \right] \\ &= \frac{1}{\lambda} \int_{-\infty}^{\infty} dx f'(x) E \left[\exp - \lambda \int_0^T ds \mathbb{1}_{(B_s \leq x)} \right] \\ & [\quad] . \end{aligned}$$