

RR with consistent increments *versus* crude MC

- **Extreme** at-the-money Call in a B - S model with

$$r = 0.15, \quad \sigma = 1.0, \quad T = 1, \quad X_0 = K = 100.$$

- Reference price = $C_0^{BS} = 42.9571$.
- Euler scheme with step size $h = \frac{T}{n}$, $n = 8$.
- **Same complexity** $\Rightarrow$ B - S Euler scheme $\rightsquigarrow 3M$ samples *versus* RR -Extrapolation meta-scheme $\rightsquigarrow M$ **consistent** samples.

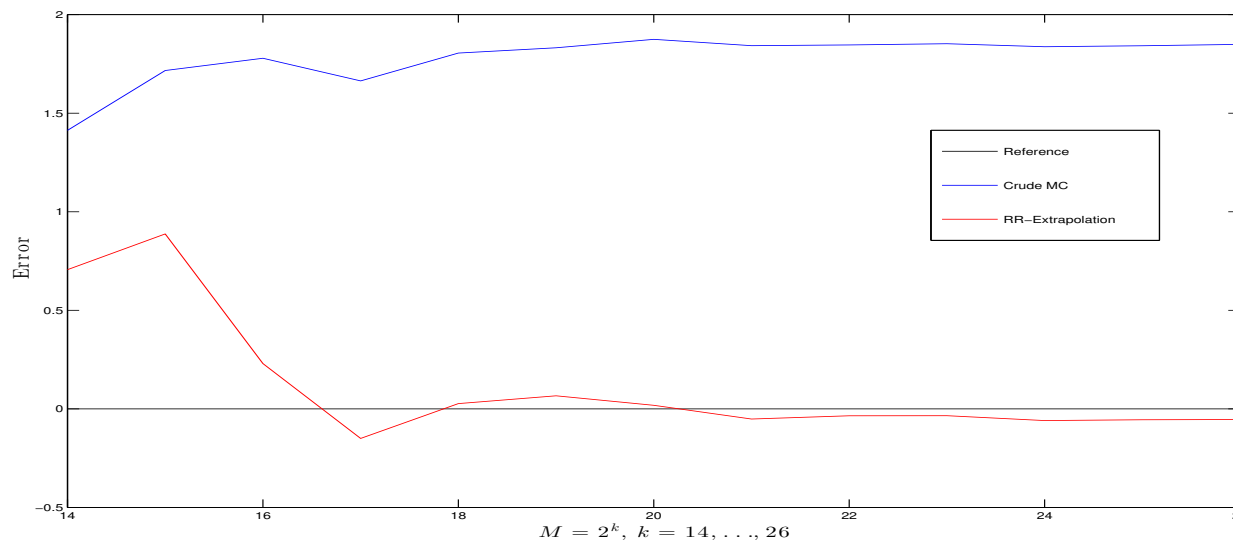


Figure: Richardson-Romberg extrapolation with **consistent** Brownian increments: **solid blue** = Crude MC on Euler scheme ($3M$); **solid red** = RR -Extrapol (M).

RR with non-consistent increments vs crude MC

- **Extreme** at-the-money Call in a B - S model with

$$r = 0.15, \quad \sigma = 1.0, \quad T = 1, \quad X_0 = K = 100$$

- Reference price = $C_0^{BS} = 42.9571$.
- Euler scheme with step size $h = \frac{T}{n}$, $n = 8$.
- **Same complexity** $\Rightarrow$ Euler $\rightsquigarrow 3M$ versus RR-Extrapolation $\rightsquigarrow M$ sample paths.

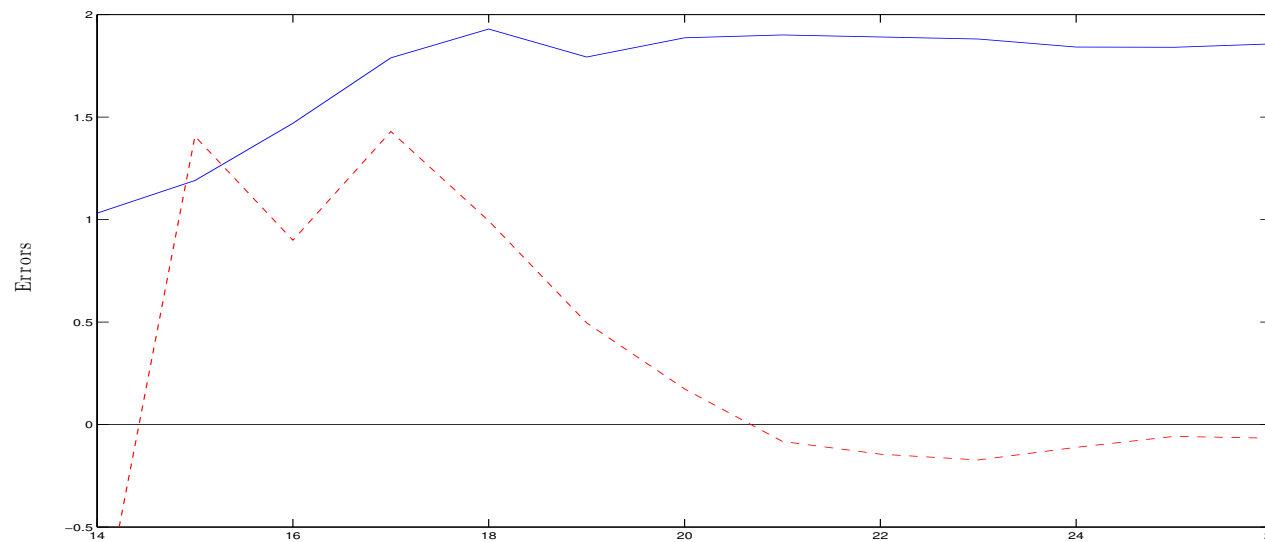


Figure: Richardson-Romberg extrapolation with $M = 2^k$, $k = 14, \dots, 26$ non-consistent Brownian increments: solid blue = Crude MC ($3M$); dotted red = RR-Extrapol (M)

The case of path-dependent payoffs

- No similar general weak error result holds path-dependent functionals $F(X)$ where

$$F : \mathbb{D}([0, T], \mathbb{R}^d) = \{x : [0, T] \rightarrow \mathbb{R}^d, \text{ càdlàg} \} \longrightarrow \mathbb{R}_+.$$

- Typical payoff functionals in Finance:

- ▶ Asian payoffs: $F(x) = f\left(x(T), \frac{1}{T} \int_0^T x(t) dt\right).$

- ▶ Lookback payoffs: $F(x) = f\left(x(T), \sup_{t \in [0, T]} x(t)\right),$
 $F(x) = f\left(x(T), \inf_{t \in [0, T]} x(t)\right).$

- ▶ Barrier payoffs:

- ★ $F(x) = f(x(T)) \mathbf{1}_{\{\sup_{t \in [0, T]} x(t) \leq L\}}$ or $F(x) = f(x(T)) \mathbf{1}_{\{\inf_{t \in [0, T]} x(t) \geq L\}}$
are **knock-out-payoffs**

- ★ $F(x) = f(x(T)) \mathbf{1}_{\{\sup_{t \in [0, T]} x(t) \geq L\}}$ or $F(x) = f(x(T)) \mathbf{1}_{\{\inf_{t \in [0, T]} x(t) \leq L\}}$
are **knock-in-payoffs**.

- ★ More generally $F(x) = f(x(T)) \mathbf{1}_{\{\tau_D > T\}}$

with $\tau_D(x) = \inf \{s : x(s) \notin D\}, \quad D \subset \mathbb{R}^d, \quad D \text{ open set.}$

- Keep in mind that the problem is to “expand” for the Euler schemes of a Brownian diffusion process $X = (X_t)_{t \in [0, T]}$

$$\mathbb{E} F((\bar{X}_t)_{t \in [0, T]}) - \mathbb{E} F((X_t)_{t \in [0, T]}) = ? \quad \text{as} \quad h = \frac{T}{n} \rightarrow 0,$$

or

$$\mathbb{E} F((\tilde{X}_t)_{t \in [0, T]}) - \mathbb{E} F((X_t)_{t \in [0, T]}) = ? \quad \text{as} \quad h = \frac{T}{n} \rightarrow 0.$$

- This question has been investigated by several authors (e.g. E. Gobet for barrier like options) with (very) partial weak error results at order 1 (see detailed written notes), typically of the form:

- **Genuine Euler scheme** (a priori **not** simulable/computable):

$$\mathbb{E} F((\bar{X}_t)_{t \in [0, T]}) = \mathbb{E} F((X_t)_{t \in [0, T]}) + c_1 h + o(h)$$

- **Stepwise constant Euler scheme** (a priori simulable/computable):

$$\mathbb{E} F((\tilde{X}_t)_{t \in [0, T]}) = \mathbb{E} F((X_t)_{t \in [0, T]}) + c_1 h^{\frac{1}{2}} + o(h^{\frac{1}{2}}).$$

Theorem (Example of barrier options)

(a) If the domain D is bounded and has a smooth enough boundary (in fact $\mathcal{C}^3$), if $b \in \mathcal{C}^3(\mathbb{R}^d, \mathbb{R}^d)$, $\sigma \in \mathcal{C}^3(\mathbb{R}^d, \mathcal{M}(d, q, \mathbb{R}))$, σ uniformly elliptic on D (i.e. $\sigma\sigma^*(x) \geq \varepsilon_0 I_d$, $\varepsilon_0 > 0$), then, for every bounded Borel function f vanishing in a neighborhood of ∂D ,

$$\mathbb{E}\left(f(X_T)\mathbf{1}_{\{\tau_D(X) > T\}}\right) - \mathbb{E}\left(f(\tilde{X}_T^n)\mathbf{1}_{\{\tau_D(\tilde{X}^n) > T\}}\right) = O\left(\frac{1}{\sqrt{n}}\right) \text{ as } n \rightarrow +\infty$$

where $\tilde{X}$ denotes the stepwise constant Euler scheme.

(b) If, furthermore, b and σ are $\mathcal{C}^5$ and D is a half-space, then the genuine Euler scheme $\bar{X}^n$ satisfies

$$\mathbb{E}\left(f(X_T)\mathbf{1}_{\{\tau_D(X) > T\}}\right) - \mathbb{E}\left(f(\bar{X}_T^n)\mathbf{1}_{\{\tau_D(\bar{X}^n) > T\}}\right) = O\left(\frac{1}{n}\right) \text{ as } n \rightarrow +\infty.$$

- Unfortunately these assumptions are not satisfied by standard barrier options.

Lookback style options (conjectures and results)

- It is “suggested” in Seumen-Tonou’s PhD (with a proof when $X = W$, otherwise a **conjecture**) that if $b, \sigma \in \mathcal{C}_b^4(\mathbb{R}, \mathbb{R})$, σ is uniformly elliptic and $f \in \mathcal{C}_{pol}^{4,2}(\mathbb{R}^2)$ (existing partial derivatives with polynomial growth):

$$\mathbb{E}\left(f(X_T, \max_{t \in [0, T]} X_t)\right) - \mathbb{E}\left(f(\tilde{X}_T^n, \max_{0 \leq k \leq n} \tilde{X}_{t_k}^n)\right) = O\left(\frac{1}{\sqrt{n}}\right) \text{ as } n \rightarrow +\infty.$$

- A similar improvement – $O(\frac{1}{n})$ rate – as above can be expected (but also **remains a conjecture**) when replacing $\tilde{X}$ by the continuous Euler scheme $\bar{X}^n$, namely

$$\mathbb{E}\left(f(X_T, \max_{t \in [0, T]} X_t)\right) - \mathbb{E}\left(f(\bar{X}_T^n, \max_{t \in [0, T]} \bar{X}_t^n)\right) = O\left(\frac{1}{n}\right) \text{ as } n \rightarrow +\infty.$$

- More recently, Alfonsi et al. obtained $O(n^{-(\frac{2}{3}-\eta)})$ for every $\eta > 0$.
- Relies on transport inequalities and the Wasserstein metric.

- Nevertheless, is it possible to **simulate some specific** functionals of the **genuine** Euler scheme?
- Yes. . . when $F(x) = f(x(T), \sup_{t \in [0, T]} x(t))$
- But it is a long way from home. . .

The Brownian bridge

Theorem (Brownian bridge)

Let $W = (W_t)_{t \geq 0}$ be a standard Brownian motion.

(a) Let $T > 0$. Then, the so-called standard Brownian bridge on $[0, T]$ defined by

$$Y_t^{W,T} := W_t - \frac{t}{T} W_T, \quad t \in [0, T], \quad (1)$$

is an $\mathcal{F}_T^W$ -measurable centered Gaussian process, independent of $(W_{T+s})_{s \geq 0}$, whose distribution is characterized by its covariance structure

$$\mathbb{E} (Y_s^{W,T} Y_t^{W,T}) = s \wedge t - \frac{st}{T} = \frac{(s \wedge t)(T - s \vee t)}{T}, \quad 0 \leq s, t \leq T.$$

To be continued (...)

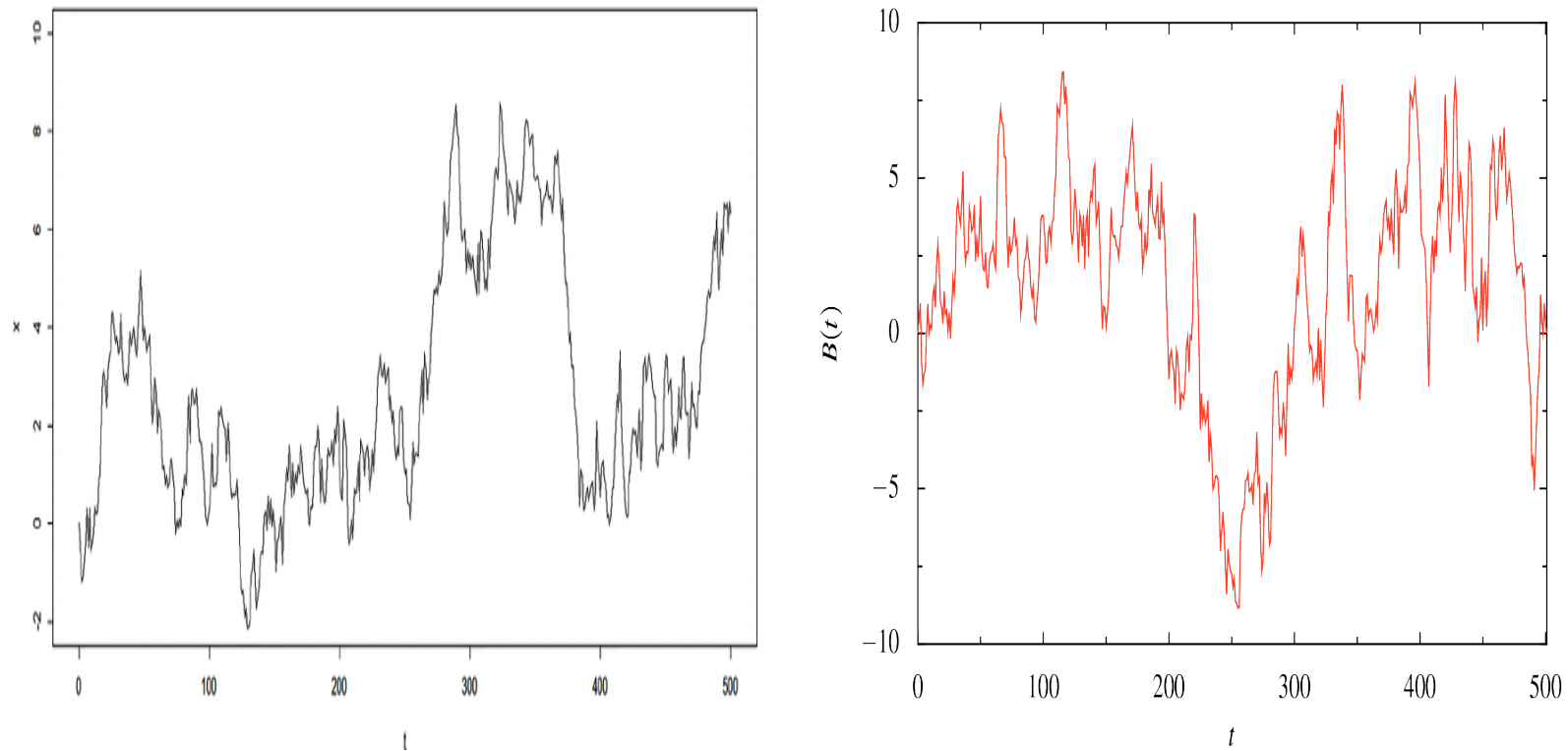


Figure: $T = 300$. Left : Standard Brownian motion path (black). Right: Standard Brownian bridge paths (red).

Proof

- $(Y_t^{W,T})_{t \in [0, T]}$ is clearly centered since W is. Starting from $\mathbb{E} W_s W_t = s \wedge t, s, t \in [0, T] \dots$
- Elementary computations show (**Exercise!**) that

$$\begin{aligned} \mathbb{E}(Y_t^{W,T} Y_s^{W,T}) &= \mathbb{E} W_t W_s - \frac{s}{T} \mathbb{E} W_t W_T - \frac{t}{T} \mathbb{E} W_s W_T + \frac{st}{T^2} \mathbb{E} W_T^2 \\ &= s \wedge t - \frac{st}{T} - \frac{ts}{T} + \frac{ts}{T} \\ &= s \wedge t - \frac{ts}{T} = \frac{(s \wedge t)(T - s \vee t)}{T}. \end{aligned}$$

- Let $\mathbb{G}_W = \overline{\text{span}\{W_t, t \geq 0\}}^{L^2(\mathbb{P})}$ be the closed vector subspace of $L^2(\Omega, \mathcal{A}, \mathbb{P})$ spanned by the Brownian motion W .
- As W is a centered Gaussian process: **independence** $\iff$ absence of correlation in $\mathbb{G}_W$.
- $Y_t^{W,T}$ belongs to this space by construction.
- As, for every $u \geq T$, $\mathbb{E}(Y_t^{W,T} W_u) = 0$, $Y_t^{W,T} \perp \text{span}(W_u, u \geq T)$.
- Consequently, $Y^{W,T}$ is independent of $(W_{T+u})_{u \geq 0}$.

Theorem (Brownian bridge)

(b) Let $T_0, T_1 \in (0, +\infty)$, $T_0 < T_1$. Then

$$\mathcal{L} \left((W_t)_{t \in [T_0, T_1]} \mid W_s, s \notin (T_0, T_1) \right) = \mathcal{L} \left((W_t)_{t \in [T_0, T_1]} \mid W_{T_0}, W_{T_1} \right)$$

so that $(W_t)_{t \in [T_0, T_1]}$ and $(W_s)_{s \notin (T_0, T_1)}$ are independent given (W_{T_0}, W_{T_1}) . Moreover, this conditional distribution is given by

$$\begin{aligned} \mathcal{L} \left((W_t)_{t \in [T_0, T_1]} \mid W_{T_0} = x, W_{T_1} = y \right) \\ = \mathcal{L} \left(\underbrace{x + \frac{t - T_0}{T_1 - T_0} (y - x)}_{\text{interpolation}} + \underbrace{(Y_{t - T_0}^{B, (T_1 - T_0)})_{t \in [T_0, T_1]}}_{\text{Brownian bridge}} \right), \end{aligned}$$

where B is a generic standard Brownian motion.

- Pathwise $B_t = W_{T_0+t} - W_{T_0}$.

Proof

- Write

$$W_t = W_{T_0} + W_{t-T_0}^{(T_0)},$$

where $W_t^{(T_0)} = W_{T_0+t} - W_{T_0}$ standard B.M $\perp\!\!\!\perp \mathcal{F}_{T_0}^W$.

- Check that

$$W_s^{(T_0)} = \frac{s}{T_1 - T_0} W_{T_1 - T_0}^{(T_0)} + Y_s^{W^{(T_0)}, T_1 - T_0}.$$

- Plugging this identity into the above equality at time $s = t - T_0$ leads to

$$W_t = W_{T_0} + \frac{t - T_0}{T_1 - T_0} (W_{T_1} - W_{T_0}) + Y_{t-T_0}^{W^{(T_0)}, T_1 - T_0}.$$

- $\tilde{Y} := (Y_{t-T_0}^{W^{(T_0)}, T_1 - T_0})_{t \in [T_0, T_1]}$ is a centered Gaussian process, $\mathcal{F}_{T_1 - T_0}^{W^{(T_0)}}$ -measurable by (a), hence independent of $\mathcal{F}_{T_0}^W$ since $W^{(T_0)}$ is.

Proof

- Consequently, $\tilde{Y} \perp\!\!\!\perp (W_t)_{t \in [0, T_0]}$. Furthermore, $\tilde{Y} \perp\!\!\!\perp (W_{T_1 - T_0 + u}^{(T_0)})_{u \geq 0}$ by (a).
- Hence it is $L^2(\mathbb{P})$ -orthogonal to $W_{T_1+u} - W_{T_0}$, $u \geq 0$, in $\mathbb{G}_W$.
- As it is also orthogonal to W_{T_0} in $\mathbb{G}_W$ since W_{T_0} is $\mathcal{F}_{T_0}^W$ -measurable, it is orthogonal to $W_{T_1+u} = W_{T_1 - T_0 + u}^{(T_0)} + W_{T_0}$, $u \geq 0$.
- Which in turn implies independence of $\tilde{Y}$ and $(W_{T_1+u})_{u \geq 0}$ since all these random variables lie in $\mathbb{G}_W$.
- Finally, the same argument – in $\mathbb{G}_W$, no correlation implies independence – implies that $\tilde{Y}$ is independent of $(W_s)_{s \in \mathbb{R}_+ \setminus (T_0, T_1)}$ *i.e.* of the σ -field $\sigma(W_s, s \notin (T_0, T_1))$.
- The end of the proof follows from the above identity.

Bridge of the Euler scheme (diffusion bridge)

Let $\bar{X} = (\bar{X}_t^n)_{t \in [0, T]}$ be the **genuine Euler scheme** and $t_k^n = \frac{kT}{n}$, $k = 0 : n$.

Theorem (Euler scheme bridge)

Assume that $\sigma(t, x) \neq 0$ for every $t \in [0, T]$, $x \in \mathbb{R}$.

(a) The processes $(\bar{X}_t^n)_{t \in [t_k^n, t_{k+1}^n]}$, $k = 0, \dots, n-1$, are *conditionally independent given the discrete time Euler scheme* $\bar{X}_{t_k^n}^n$, $k = 0, \dots, n$.

(b) Furthermore, for every $k \in \{0, \dots, n\}$, the conditional distribution

$$\begin{aligned} \mathcal{L}\left((\bar{X}_t^n)_{t \in [t_k^n, t_{k+1}^n]} \mid \bar{X}_{t_\ell^n}^n = x_\ell, \ell = 0, \dots, n\right) \\ = \mathcal{L}\left((\bar{X}_t^n)_{t \in [t_k^n, t_{k+1}^n]} \mid \bar{X}_{t_k^n}^n = x_k, \bar{X}_{t_{k+1}^n}^n = x_{k+1}\right) \\ = \mathcal{L}\left(\left(x_k + \frac{n(t - t_k^n)}{T}(x_{k+1} - x_k) + \sigma(t_k^n, x_k) Y_{t - t_k^n}^{B, T/n}\right)_{t \in [t_k^n, t_{k+1}^n]}\right) \end{aligned}$$

where $(Y_s^{B, T/n})_{s \in [0, T/n]}$ is a Brownian bridge.

(A bit) More on the Diffusion bridge

The distribution of this Gaussian process (sometimes called a diffusion bridge) is entirely characterized by:

- its expectation function $\left(x_k + \frac{n(t - t_k^n)}{T} (x_{k+1} - x_k) \right)_{t \in [t_k^n, t_{k+1}^n]}$,
- its covariance operator $\sigma^2(t_k^n, x_k) \frac{(s \wedge t - t_k^n)(t_{k+1}^n - s \vee t)}{t_{k+1}^n - t_k^n}$,
 $s, t \in [t_k^n, t_{k+1}^n]$.

Supremum of a diffusion bridge

Proposition

The distribution of the supremum of the Brownian bridge starting at 0 and arriving at y at time T , defined by $Y_t^{W,T,y} = \frac{t}{T}y + W_t - \frac{t}{T}W_T$ on $[0, T]$, is given by

$$\mathbb{P}\left(\sup_{t \in [0, T]} Y_t^{W,T,y} \leq z\right) = \begin{cases} 1 - \exp\left(-\frac{2}{T}z(z - y)\right) & \text{if } z \geq \max(y, 0), \\ 0 & \text{if } z \leq \max(y, 0). \end{cases}$$

The key of the proof is the [reflection principle](#).