

The γ -compounding random walk

[2] [1]

This sum can be done exactly at least for the case $\gamma = \frac{1}{2}$ (details later):

$$\sum_{n=0}^T \binom{T}{n} = 2^T \quad (1) \quad x_T = \left(\sqrt{X_0} - 1 + \sqrt{P(T, \sqrt{g+r}, \sqrt{g-r})} \right)^2, \quad (10)$$

$$\sum_{n=0}^T \binom{T}{n} n = \sum_{n=0}^T \binom{T}{n} (T-n) = T 2^{T-1} \quad (2) \quad \text{where}$$

$$\sum_{n=0}^T \binom{T}{n} n^2 = \sum_{n=0}^T \binom{T}{n} (T-n)^2 = T(T+1) 2^{T-2}. \quad (3) \quad P(n, x, y) = \frac{1}{4} n(n+1)x^2 + \frac{1}{2} n(n-1)xy - n(n-1)x + \frac{1}{4} n(n+1)y^2 - n(n-1)y + (n-1)^2.$$

Define the generalised exponential and logarithm as

$$\exp_{\gamma}(x) = \begin{cases} (1 + \gamma x)^{\frac{1}{\gamma}} & 0 < \gamma \leq 1 \\ \exp(x) & \gamma = 0 \end{cases} \quad (4)$$

$$\log_{\gamma}(x) = \begin{cases} \frac{1}{\gamma} (x^{\gamma} - 1) & 0 < \gamma \leq 1 \\ \log(x) & \gamma = 0 \end{cases}, \quad (5)$$

For large enough T we find

$$\mathbb{E}[x_T] \sim \frac{1}{4} (\sqrt{g+r} + \sqrt{g-r} - 2)^2 T^2. \quad (11)$$

The *typical* value of x_T can be found by finding n^* , the value of n that maximises the probability, Eq. (8). This is

and the generalised compounding operator, \otimes , as

$$x \otimes y = \exp_{\gamma} [\log_{\gamma}(x) + \log_{\gamma}(y)]. \quad (6)$$

$$n^* = \arg \max_n \binom{T}{n} = \frac{T}{2}.$$

We are interested in studying the gamma-compounding random walk in discrete time with growth factors $g+r$ and $g-r$ occurring with equal probability:

$$x_{t+1} = \begin{cases} x_t \otimes (g+r) & \text{with probability } \frac{1}{2} \\ x_t \otimes (g-r) & \text{with probability } \frac{1}{2}. \end{cases} \quad (7)$$

Thus the typical value of x_T is

$$\begin{aligned} \tilde{x}_T &= X_0 \otimes \exp_{\gamma} \left[\frac{T}{2} (\log_{\gamma}(g+r) + \log_{\gamma}(g-r)) \right] \\ &= \left(\frac{T}{2} ((g-r)^{\gamma} + (g+r)^{\gamma} - 2) + X_0^{\gamma} \right)^{1/\gamma}. \end{aligned} \quad (12)$$

with $x_0 = X_0$.

If, after playing T rounds of the game, we experience n "wins" (and $T-n$ "losses"), then x_T will take the value

For large enough T , we find

$$x_T = X_0 \otimes \underbrace{(g+r) \otimes \dots \otimes (g+r)}_{n\text{-times}} \otimes \underbrace{(g-r) \otimes \dots \otimes (g-r)}_{T-n\text{-times}} \sim \left(\frac{1}{2} ((g-r)^{\gamma} + (g+r)^{\gamma} - 2) \right)^{\frac{1}{\gamma}} T^{\frac{1}{\gamma}}. \quad (13)$$

$$\begin{aligned} &= X_0 \otimes \exp_{\gamma} [n \log_{\gamma}(g+r)] \otimes \exp_{\gamma} [(T-n) \log_{\gamma}(g-r)] \\ &= X_0 \otimes \exp_{\gamma} [n \log_{\gamma}(g+r) + (T-n) \log_{\gamma}(g-r)] \end{aligned}$$

Note that for $\gamma = \frac{1}{2}$, this agrees with Eq. (11) which suggests that for the γ -compounding random walk, the expected value is representative.

The probability of this value is

From Eq. (7), the quantity $y_t = \log_{\gamma} x_t$ follows a simple additive random walk:

$$p(n) = \binom{T}{n} \left(\frac{1}{2} \right)^T, \quad (8)$$

$$y_{t+1} = \begin{cases} y_t + a & \text{with probability } \frac{1}{2} \\ y_t + b & \text{with probability } \frac{1}{2}, \end{cases} \quad (14)$$

where $\binom{T}{n}$ is the binomial coefficient - the number of ways in which n wins can occur in a sequence of T rounds of the game. The expectation value of x_T is therefore

where

$$a = \log_{\gamma}(g+r)$$

$$b = \log_{\gamma}(g-r).$$

$$\mathbb{E}[x_T] = \sum_{n=0}^T \binom{T}{n} \left(\frac{1}{2} \right)^T X_0 \otimes \exp_{\gamma} [n \log_{\gamma}(g+r) + (T-n) \log_{\gamma}(g-r)]. \quad (9)$$

If, after playing T rounds of the game, we experience n "wins" (and $T-n$ "losses"), then y_T will take the value

$$y_T = n a + (T-n) b.$$

The corresponding probability is again given by Eq. (8). The expectation value of y_T is

$$\begin{aligned}
 \mathbb{E}[y_T] &= \sum_{n=0}^T \binom{T}{n} \left(\frac{1}{2}\right)^T [n a + (T - n) b] \\
 &= \frac{T}{2} \left(a \sum_{n=0}^T \binom{T}{n} n + b \sum_{n=0}^T \binom{T}{n} (T - n) \right) \\
 &= \frac{T}{2} (a + b) \\
 &= \frac{T}{2} (\log_\gamma(g + r) + \log_\gamma(g - r)). \quad (15)
 \end{aligned}$$

where the second-but-last line follows from the identity

Eq. (2). We then find that

$$\begin{aligned}
 \exp_\gamma(\mathbb{E}[\log_\gamma(x_T)]) &= \exp_\gamma \left[\frac{T}{2} (\log_\gamma(g + r) + \log_\gamma(g - r)) \right] \\
 &= \left(\frac{1}{2} ((g - r)^\gamma + (g + r)^\gamma - 2) \right)^{\frac{1}{\gamma}} T^{\frac{1}{\gamma}}. \quad (16)
 \end{aligned}$$

Again, seems to coincide with the typical value. Something to figure out here.

References

- [1] Peter Carr and Umberto Cherubini. Generalized compounding and growth optimal portfolios reconciling Kelly and Samuelson. *The Journal of Derivatives*, 30(2):74–93, 2022.
- [2] Sidney Redner. Random multiplicative processes: An elementary tutorial. *American Journal of Physics*, 58(3):267–273, 1990.