

Feynman-Kac :

Assume that ^① $V(t, S)$ solves a boundary value problem:

$$\frac{\partial V(t, S)}{\partial t} + \mu(t, S) \frac{\partial V(t, S)}{\partial S} + \frac{1}{2} \sigma^2(t, S) \frac{\partial^2 V}{\partial S^2} - r V(t, S) = 0$$

$$V(T, S) = G(S)$$

^② and that the process S follows the dynamics.

$$dS = \mu(t, S)dt + \sigma(t, S)dX(t), \quad S(0) = S_0$$

Then, the function V has a representation as an expectation

$$\begin{aligned} \mu(t, S) &= \mu(t, S) \\ \sigma(t, S) &= \sigma(t, S) \end{aligned}$$

$$V(t, S) = \mathbb{E} \left[e^{-r(T-t)} G(S_T) \mid \mathcal{F}_t \right]$$

In the Black-Scholes model we saw yesterday

$$V(t, S) = e^{-r(T-t)} \mathbb{E}^\mathbb{Q} [G(S_T) | \mathcal{F}_t]$$

where S_t follows the dynamics:

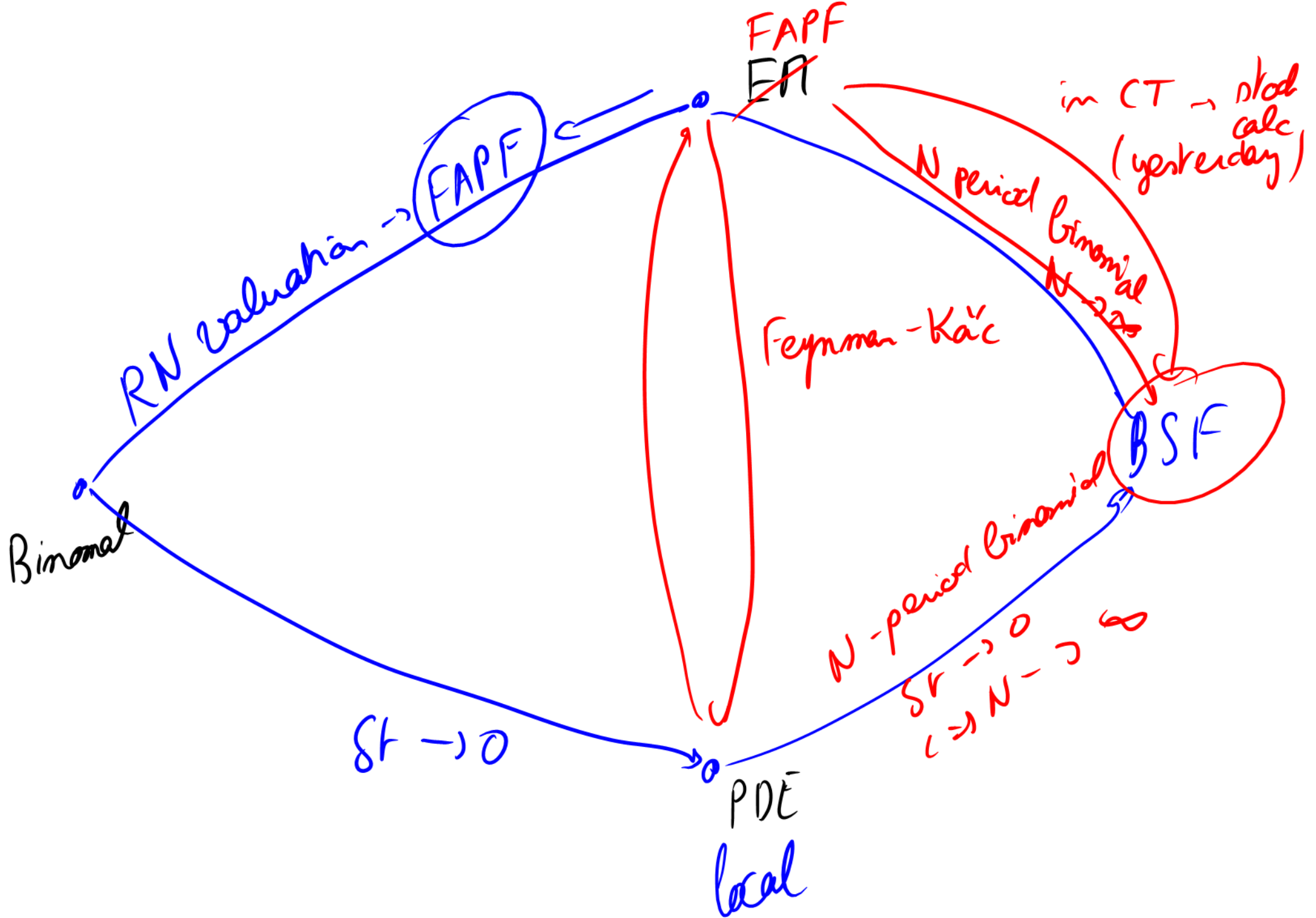
$$dS_t = r S_t dt + \sigma S_t dX^\mathbb{Q}(t)$$

→ By Feynman-Kac, $V(t, S)$ solves the boundary problem:

$$\left[\frac{\partial V}{\partial t} + r S \frac{\partial V}{\partial S} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} - r V \right] = 0$$

$$V(T, S) = G(S)$$

$$X_t^\mathbb{Q} = \left(X_t^\mathbb{P} + \int_0^t \theta(s) ds \right)$$



Δ -hedging / No Arb

- 1) You create a portfolio

$$\Pi = V - \Delta S$$

Our objective is to hedge the risk so Π becomes a hedged portfolio

- 2) Π will be hedged if it is riskless, that is, its value in the up state and down state is the same

$$\Pi_u = \Pi_d \quad (\Rightarrow) \quad V_u - \Delta S_u = V_d - \Delta S_d$$

$$\Rightarrow \quad \Delta = \frac{V_u - V_d}{S_u - S_d}$$

3) Our portfolio is now risk-free. So, to prevent arbitrage, it must earn the risk-free rate

$$\Pi_u = \Pi_d = (1 + r\delta t) \Pi_0$$

$$\Leftrightarrow \Pi_u = \frac{1}{D} \Pi_0$$

$$\Leftrightarrow V_u - \Delta S_u = \frac{1}{D} (V_0 - \Delta S_0)$$

$$\Leftrightarrow V_u - \frac{V_u - V_d}{(u-d)S_0} = \frac{1}{D} \left(V_0 - \frac{V_u - V_d}{(u-d)S_0} S_0 \right)$$

$$\Leftrightarrow \dots \quad \Leftrightarrow$$

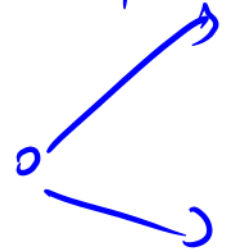
formula (1)

Risk Neutral Valuation

- On average, the stock must return the risk-free rate

$$\mathbb{E}^{RN}[S_T]$$

$$= (1 + r_{St}) S_0$$



$$\Rightarrow p^* S_u + (1 - p^*) S_d = (1 + r_{St}) S_0$$

$$\Rightarrow p^* S_0 u + (1 - p^*) S_0 d = (1 + r_{St}) S_0$$

$$\Rightarrow p^* = \frac{\frac{1}{1+r_{St}} - d}{u - d}$$

RN probability

For the Option:

$$\mathbb{E}^{RN}[V_T] = (1 + r\delta t) V_0$$

$$\Leftrightarrow p^* V_u + (1 - p^*) V_d = (1 + r\delta t) V_0$$

$$\Leftrightarrow V_0 = D \left[\underbrace{p^* V_u + (1 - p^*) V_d}_{\text{Payoffs}} \right]$$

$$\begin{array}{lcl}
 0 < P_1 < 1 & \rightarrow & P_1 \\
 0 < P_2 < 1 & \rightarrow & P_2
 \end{array}
 \Bigg) \text{ equivalent}$$

Let's try to implement what we saw last night in the humble binomial model.

• \mathbb{P} -measure $\left(\begin{array}{c} \nearrow S_0^u \\ \searrow S_0^d \end{array} \right)$ NOT a Martingale

• Look for a measure \mathbb{Q} such that the discounted stock price is a martingale \rightarrow find \mathbb{Q} such that

$$\mathbb{E}^{\mathbb{Q}}[DS_T] = S_0$$

Martingale condition
 $0 < q < 1$

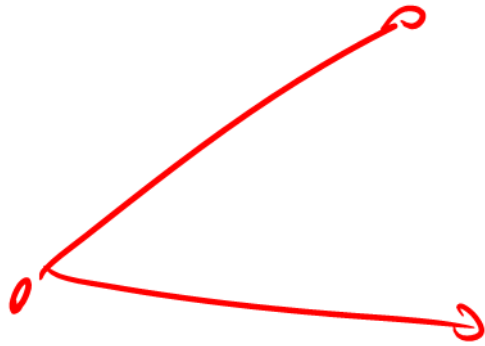
~~$$\mathbb{E}^{\mathbb{Q}}[DS_T | \mathcal{F}_t] = D_t S_t$$~~

$$\mathbb{Q} \rightarrow q$$

~~$$= q DS_0^u + (1-q) DS_0^d = S_0$$~~

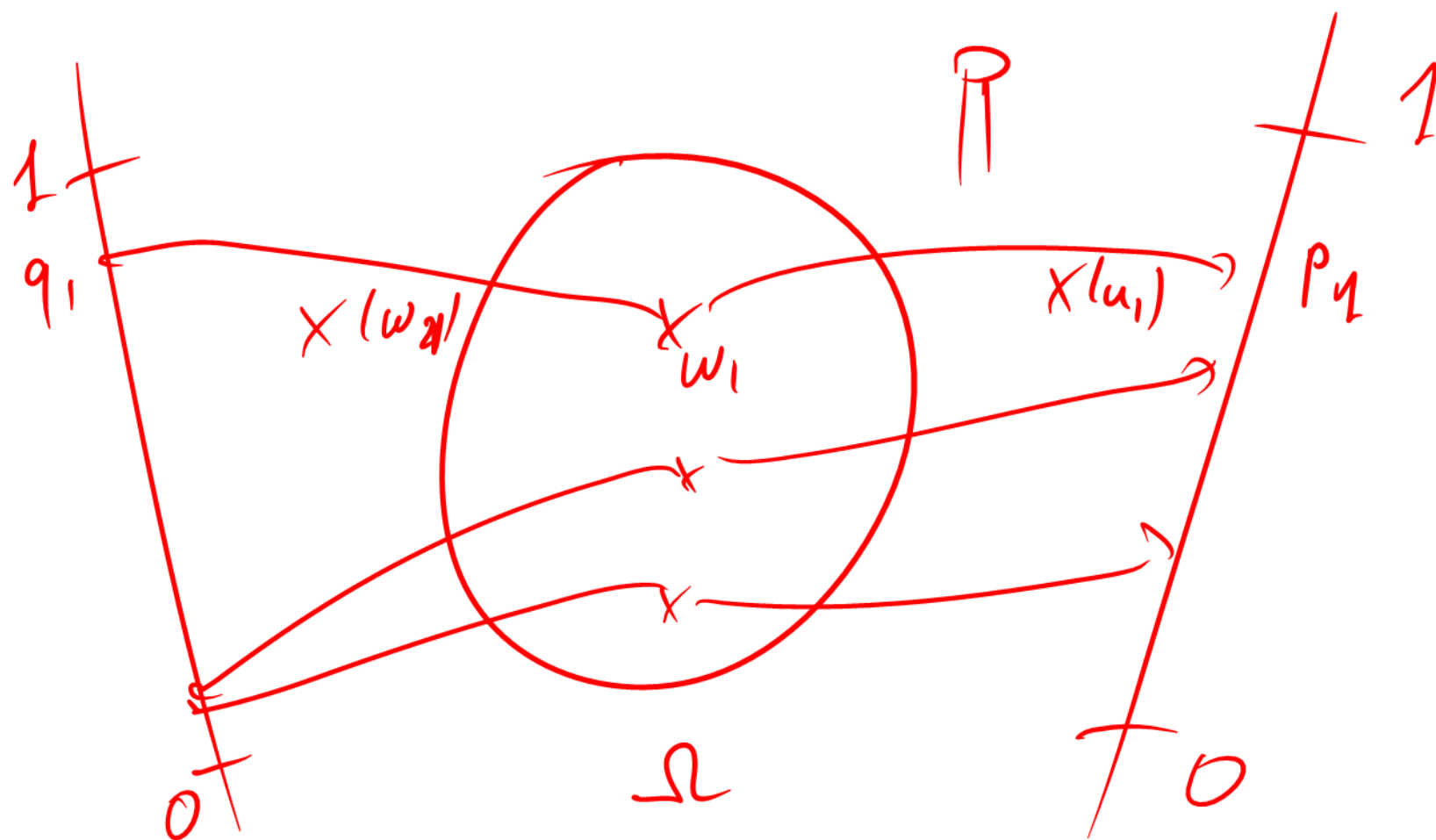
$$\Leftrightarrow q = \frac{1/d - d}{u - d} = p^*$$

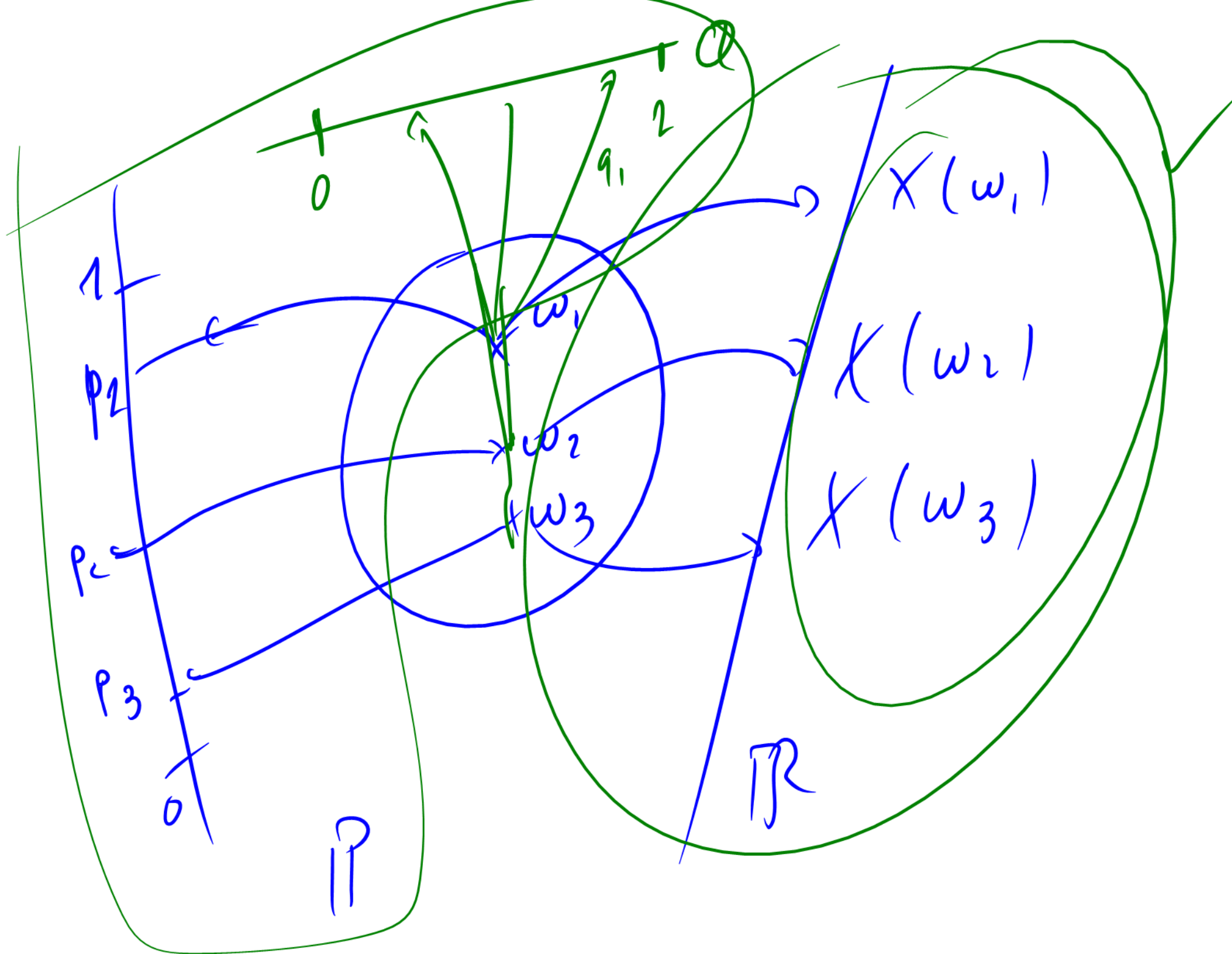
- ① $p^* = q$ $RN \equiv E \Pi \Pi$
- ② There is a UNIQUE UE $E \Pi \Pi \dots$



$$\mu = \frac{n}{6}$$

$$\begin{array}{l} p \in (0, 1) \\ \downarrow \\ p_1 \in (0, 1) \\ \downarrow \\ p_2 \in (0, 1) \\ \vdots \end{array}$$





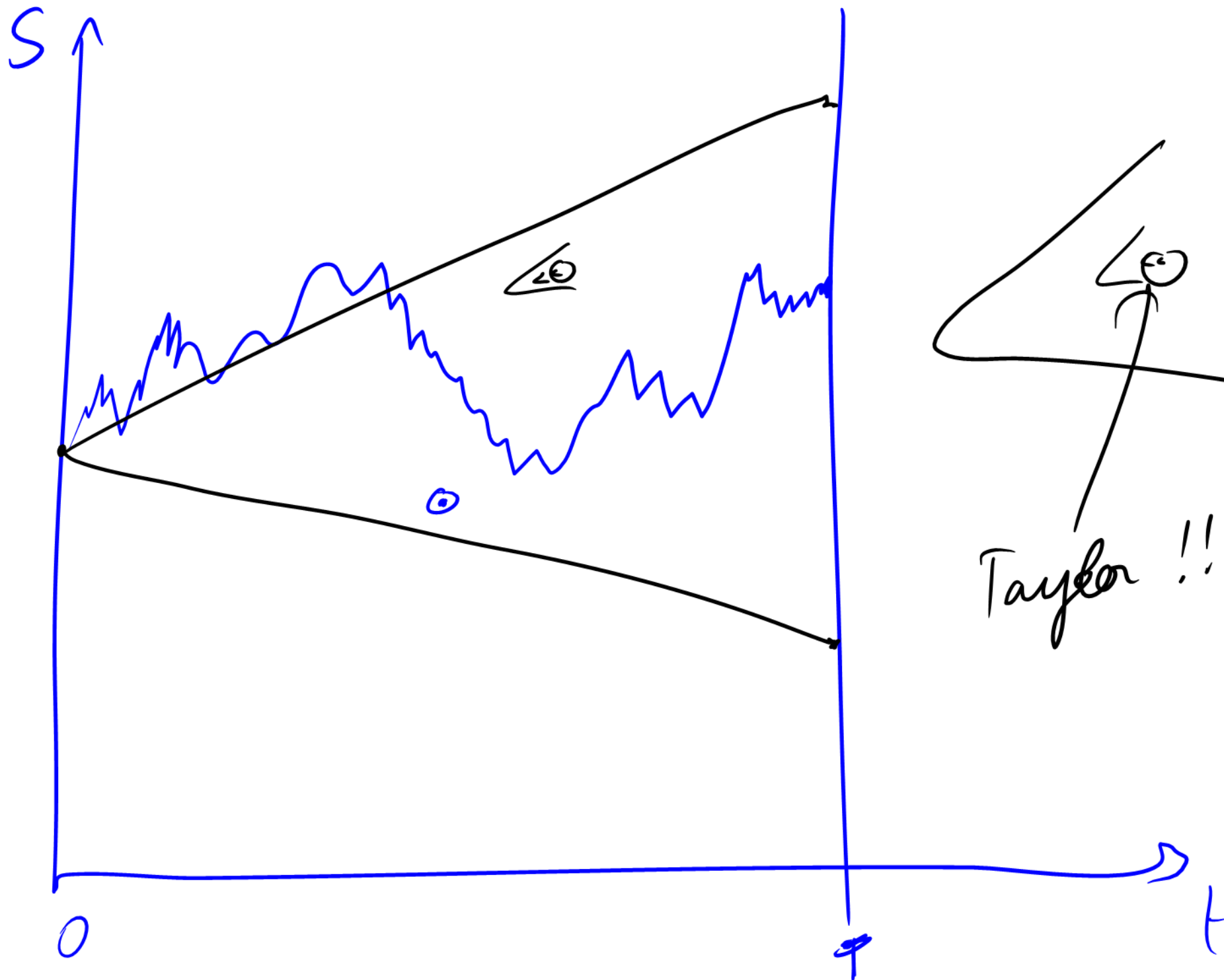
RN pricing formula

$$V_0 = D \left(\underbrace{p^*}_{q} V_u + \underbrace{(1-p^*)}_{q} V_d \right)$$

$$= q (DV_u) + (1-q) (DV_d)$$

$$V_0 = E^Q [DV_1]$$

FAPF
1-period
binomial model



Taylor !!!

$$u = e^{\sigma \sqrt{\delta t}} \approx 1 + \sigma \sqrt{\delta t} + \frac{1}{2} \sigma^2 \delta t$$

$$d = e^{-\sigma \sqrt{\delta t}} \approx 1 - \sigma \sqrt{\delta t} + \frac{1}{2} \sigma^2 \delta t$$

$$D = e^{-r \delta t} \approx 1 - r \delta t$$

$$u - d = e^{\sigma \sqrt{\delta t}} - e^{-\sigma \sqrt{\delta t}} \approx 2 \sigma \sqrt{\delta t}$$

$$\frac{1}{D} - d = e^{r \delta t} - e^{-\sigma \sqrt{\delta t}} \approx \sigma \sqrt{\delta t} + \left(r - \frac{1}{2} \sigma^2 \right) \delta t$$

$$u - \frac{1}{D} \approx \cancel{1} + \sigma \sqrt{\delta t} + \frac{1}{2} \sigma^2 \delta t - \cancel{1} - r \delta t$$

$$\approx \sigma \sqrt{\delta t} + \left(\frac{1}{2} \sigma^2 - r \right) \delta t$$

By Taylor,

$$V_u = V + \frac{\partial V}{\partial t} \delta t + \frac{\partial V}{\partial S} \delta S_u + \frac{1}{2} \frac{\partial^2 V}{\partial S^2} (\delta S)^2 + \dots$$

$$\begin{aligned} \delta S_u &= S_u - S \\ &= S(e^{\sigma \sqrt{\delta t}} - 1) \\ &\approx S(1 + \sigma \sqrt{\delta t} + \frac{1}{2} \sigma^2 \delta t - 1) \\ &\approx S(\sigma \sqrt{\delta t} + \frac{1}{2} \sigma^2 \delta t) \end{aligned}$$

$$(\delta S_u)^2 \approx S^2 \sigma^2 \delta t$$

$$V_d = V + \frac{\partial V}{\partial t} \delta t + \frac{\partial V}{\partial S} \delta S_d + \frac{1}{2} \frac{\partial^2 V}{\partial S^2} (\delta S_d)^2$$

$$\begin{aligned} \delta S_d &= S_d - S \\ &= S e^{-\sigma \sqrt{\delta t}} - S \\ &= S(-\sigma \sqrt{\delta t} + \frac{1}{2} \sigma^2 \delta t) \end{aligned}$$

$$(\delta S_d)^2 = S^2 \sigma^2 \delta t$$

$k=2$: applying the RN valuation formula

$$V(N-2, i) = D \left[p^* V(N-1, i+1) + (1-p^*) V(N-1, i) \right]$$

$$= D \left[p^* \left(D(p^* V(N, i+2) + (1-p^*) V(N, i+1)) \right) + (1-p^*) \left(D(p^* V(N, i+1) + (1-p^*) V(N, i)) \right) \right]$$

$$= D^2 \left[p^{*2} V(N, i+2) + 2p^*(1-p^*) V(N, i+1) + (1-p^*)^2 V(N, i) \right]$$

↑

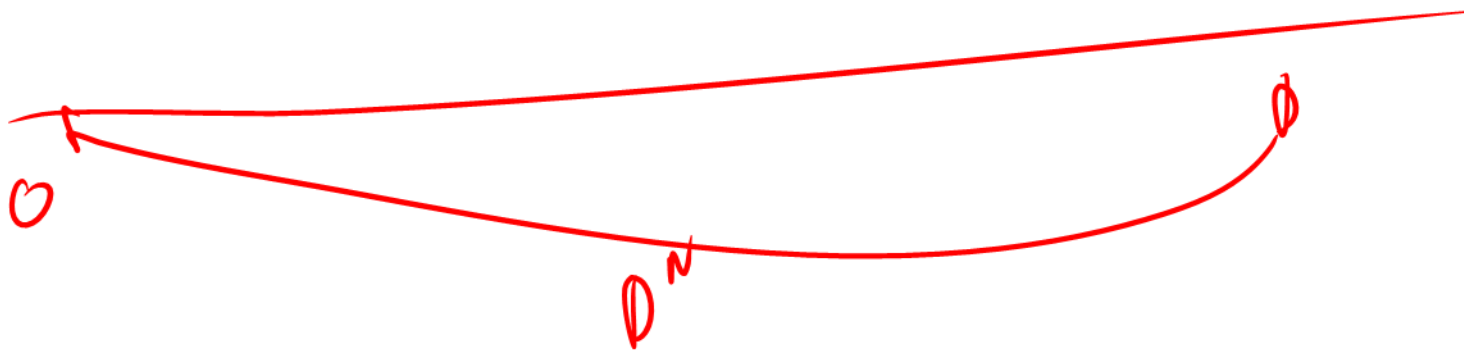


$$D^N \sum_{i=0}^N C_N^i (p^*)^i (1-p^*)^{N-i} p(X_i)$$

$$= D^N E^{B(N, p^*)} [p(X)]$$

$$\text{Payoff} [S(N, i) - E, 0]$$

Payoff



$$V_0 = D^N \mathbb{E}^{B(N, P^*)} \left[\underbrace{\max[S(N, i) - E, 0]}_{(S(N, i) - E) \times \mathbb{1}_{\{S(N, i) - E > 0\}}} \right]$$

$$= D^N \mathbb{E}^{B(N, P^*)} \left[S(N, i) \mathbb{1}_{\{S(N, i) - E > 0\}} \right] \quad \textcircled{1} \text{ Tough!}$$

$$+ D^N \mathbb{E}^{B(N, P^*)} \left[E \mathbb{1}_{\{S(N, i) > E\}} \right] \quad \textcircled{2} \text{ Easy!}$$

$$\textcircled{2}. D^N \mathbb{E}^{B(N, P^*)} \left[\mathbb{E} \left[\mathbb{1}_{\{S(N) > \epsilon\}} \right] \right]$$

$$= D^N \mathbb{E}^{B(N, P^*)} \left[\mathbb{1}_{\{S(N) > \epsilon\}} \right]$$

$$= D^N P^* \left[S(N) > \epsilon \right]$$

$\rightarrow \mathbb{E} e^{-\pi T} N(d_2)$

$N \rightarrow \infty$

$$(1) D^N E^{B(N, p^*)} [S(N) \mathbb{1}_{\{S(N) > \epsilon\}}]$$

$$= S_0 D^N \sum_{i=0}^N C_N^i (p^*)^i (1-p^*)^{N-i} u d^{N-i} \mathbb{1}_{\{S(N) > \epsilon\}}$$

$i + N - i = N$

$$\text{Set } \bar{p} = p^* d u$$

$$(1-\bar{p}) = (1-p^*) d D$$

$$(2) S_0 \sum_{i=0}^N \frac{C_N^i (\bar{p})^i (1-\bar{p})^{N-i}}{B(N, \bar{p})} \mathbb{1}_{\{S(N) > \epsilon\}}$$

$$= S_0 E \left[\mathbb{1}_{\{S(N) > \epsilon\}} \right]$$

$\xrightarrow{N \rightarrow \infty} SN(d, u)$