### Arbitrage&Pricing

Paris Dauphine University - Master I.E.F. (272) 2023/24

### Jérôme MATHIS

www.jeromemathis.fr/a-p

LEDa

Chapter 3

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

# Chapter 3: Binomial tree with n period

Introduction

**Outline** 

- Binomial Trees: Two-Step
- Binomial tree: generalization
- Conclusion

# Chapter 3: Binomial tree with n period Outline

- Introduction
- 2 Binomial Trees: Two-Step
- 3 Binomial tree: generalization
- 4 Conclusion

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

3/6

### Introduction

- The one-period model is often too simple for practical purpose.
  - ► An individual investor has approximately 50 years of adult life when he is making choices over savings, investment and consumption.
    - \* If important investment decisions are taken every five years, we need at least a 10-period model.
  - Professional investors trade even more frequently.
    - \* A trader on a stock exchange may adjust his portfolio several times a day resulting in more than 500 investment decisions a month.

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 2 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 4 / 6

### Introduction

- The aim of this chapter is to introduce the techniques to asset pricing in a dynamic framework.
  - ▶ We use a simple set-up with the European call option as a focus asset in a discrete-time model:
    - \* to illustrate the backward recursive pricing procedure; and
    - \* to recover the option price as an unconditional expectation under risk-neutral probabilities.

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

Arbitrage&Pricing

## Chapter 3: Binomial tree with n period **Outline**

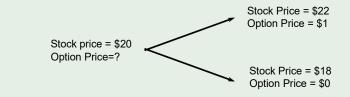
- Binomial Trees: Two-Step
  - Generalization
  - A Put Option Example
  - Delta

### Binomial Trees: Two-Step

Consider Example D of Chapter 2:

### Example

A 3-month call option on the stock has a strike price of 21.



Jérôme MATHIS (LEDa)

# **Binomial Trees: Two-Step**

Applying the formula

$$C_0 = \frac{1}{R} \left( \frac{R-d}{u-d} C_1^u + \frac{u-R}{u-d} C_1^d \right)$$

to the 3 months risk-free interest rate of 3.05%, we found the initial price of the option:

$$C_0 = \frac{1}{1.0305} \left( \frac{1.0305 - 0.9}{1.1 - 0.9} \right) \simeq 0.633$$

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 Jérôme MATHIS (LEDa) Arbitrage&Pricing

### Binomial Trees: Two-Step

- We also obtained the same initial price of the option using a risk-neutral valuation.
- Indeed, by denoting *q* the probability that gives a return on the stock equal to the risk-free rate:

$$S_0(1+r) = S_1^u q + S_1^d(1-q).$$

• The value of the option is

$$C_0 = \frac{C_1^u q + C_1^d (1 - q)}{1 + r}$$

• So that in Example  $D^{(5)}$  we obtained

$$20(1.0305) = 22q + 18(1-q).$$

so that q = 0.6525. And

$$C_0 = \frac{1 \times 0.6525 + 0(1 - 0.6525)}{1.0305} \simeq 0.6332.$$

Jérôme MATHIS (LEDa)

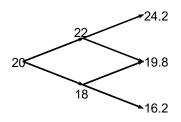
Arbitrage&Pricing

Chapter 3

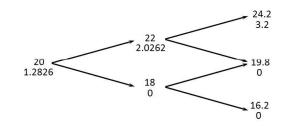
9 / 68

### Binomial Trees: Two-Step

- Let us extend this example to a two-step binomial tree.
- Assume the stock price starts at \$20 and in each of two time steps may go up by 10% or down by 10%.
  - ► Each time step is 3 months long and 3 months risk-free interest rate of 3.05%.
  - ▶ We consider a 6-month option with a strike price of \$21.



### **Binomial Trees: Two-Step**



• When the stock price is 22, the option price is

$$\frac{0.6525 \times 3.2 + 0.3475 \times 0}{1.0305} = 2.0262$$

- When the stock price is 18, the option price is zero, because it leads to two nodes where the option price is zero.
- The initial option price is

$$\frac{0.6525 \times 2.0262 + 0.3475 \times 0}{1.0305} = 1.283$$

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

11 / 68

# Binomial Trees: Two-Step Generalization

- Suppose that the risk-free interest rate is r, with continuous compounding, and the length of the time step is  $\Delta t$  years.
- We have

$$C_0 = [qC_1^u + (1-q)C_1^d]e^{-r\Delta t}$$
$$q = \frac{e^{r\Delta t} - d}{u - d}$$

$$C_1^u = [qC_2^{uu} + (1-q)C_2^{ud}]e^{-r\Delta t}$$

and

$$C_1^d = [qC_2^{du} + (1-q)C_2^{dd}]e^{-r\Delta t}$$

• So, when  $C_2^{du} = C_2^{ud}$  we obtain

$$C_0 = [q^2C_2^{uu} + 2q(1-q)C_2^{ud} + (1-q)^2C_2^{dd}]e^{-2r\Delta t}$$

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 10 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 12 / 68

# Binomial Trees: Two-Step A Put Option Example

### Question

Consider a 2-year European put with a strike price of \$52 on a stock whose current price is \$50.

We suppose that there are two time steps of 1 year, and in each time step the stock price either moves up by 20% or moves down by 20%.

We also suppose that the risk-free interest rate is 5%.

What is the initial price of the option?

Jérôme MATHIS (LEDa)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Arbitrage&Pricing

Chapter 3

Chapter 3

13 / 68

# Binomial Trees: Two-Step A Put Option Example

### Solution

# Binomial Trees: Two-Step A Put Option Example



# Binomial Trees: Two-Step A Put Option Example

Solution

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3 16 / 68

# Binomial Trees: Two-Step Delta

#### Definition

**Delta** ( $\Delta$ ) is the ratio of the change in the price of a stock option to the change in the price of the underlying stock.

- It is the number of units of the stock we should hold for each option shorted in order to create a riskless portfolio.
  - It is the same as the  $\Delta$  introduced earlier in this and previous chapters.
- The construction of a riskless portfolio is sometimes referred to as delta hedging.
- The delta of a call option is positive, whereas the delta of a put option is negative.
- The value of Δ varies from node to node.
  - ► E.g., when the stock price changes from \$18 to \$22, and the option price changes from \$0 to \$1, we have  $\Delta = \frac{1-0}{22-18} = 0.25$ .

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

17 / 68

# Chapter 3: Binomial tree with n period Outline

- 1 Introduction
- 2 Binomial Trees: Two-Step
- 3 Binomial tree: generalization
  - Basic notions on Probability
  - Setup
  - Simple portfolio strategies
  - Arbitrage and risk-neutral probability
  - Hedging derivative
- 4 Conclusion

# Binomial tree: generalization Basic notions on Probability

#### Definition

A **filtration** is a sequence of  $\sigma$ -algebra  $(\mathcal{F}_k)_{1 \leq k \leq n}$ , such that each  $\sigma$ -algebra in the sequence contains all the sets contained by the previous  $\sigma$ -algebra. Formally,  $\mathcal{F}_k \subseteq \mathcal{F}_{k+1}$ ,  $\forall k < n$ .

• A filtration models the evolution of information through time. So for example, if it is known by time k whether or not an event, E, has occurred, then we have  $E \in \mathcal{F}_k$ .

#### **Definition**

Let  $\mathcal{F} := (\mathcal{F}_k)_{1 \le k \le n}$  be a filtration. The stochastic process  $(X_k)_{1 \le k \le n}$  is  $\mathcal{F}$ -adapted, if  $X_k$  is  $\mathcal{F}_k$ -measurable for each  $k \le n$ .

• The idea is that the value of  $X_k$  is known at time k when the information represented by  $\mathcal{F}_k$  is known.

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

19 / 6

Binomial tree: generalization Basic notions on Probability

### Proposition (3.1)

If the stochastic process  $(X_k)_{1 \le k \le n}$  is  $\mathcal{F}$ -adapted, then  $X_i$  is  $\mathcal{F}_k$ -measurable for any  $i \le k$ .

#### Proof.

Straightforward.

If the stochastic process  $(X_k)_{1 \le k \le n}$  is  $\mathcal{F}$ -adapted then  $X_i$  is  $\mathcal{F}_i$ -measurable.

Since  $\mathcal{F} := (\mathcal{F}_k)_{1 \le k \le n}$  is a filtration then  $\mathcal{F}_i \subseteq \mathcal{F}_k$ ,  $\forall i \le k$ , with  $k \le n$ .

So,  $X_i$  is  $\mathcal{F}_k$ —measurable.

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 18 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 20 / 68

# Binomial tree: generalization

Basic notions on Probability

### **Definition**

The **natural filtration** of the stochastic process  $(X_k)_{1 \le k \le n}$  is given by the smallest filtration  $\mathcal{F}$  for which  $(X_k)_{1 \le k \le n}$  is  $\mathcal{F}$ —adapted.

We denote it by  $\mathcal{F}^X := (\mathcal{F}_k^X)_{1 \le k \le n}$ , with  $\mathcal{F}_k^X$  the  $\sigma$ -algebra generated by  $X_k$ .

I.e., 
$$\mathcal{F}_k^X := \sigma(X_1, X_2, ..., X_k)$$
.

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

21 / 68

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

22 / 69

# Binomial tree: generalization Basic notions on Probability

### Definition (new)

A stochastic process  $M := (M_k)_{1 \le k \le n}$  is a  $\mathcal{F}$ -martingale under  $\mathbb{P}$  if M is  $\mathcal{F}$ -adapted,

$$\mathbb{E}^{\mathbb{P}}[|M_k|]<+\infty$$
, for any  $k\leq n$ 

and

$$\mathbb{E}^{\mathbb{P}}[M_{k+1}|\mathcal{F}_k] = M_k.$$

- If the previous equality is replaced with ≤ the process tends to go down and is called a *supermartingale*. If the previous equality is replaced with ≥ the process tends to go up and is called a *submartingale*.
- So, a supermartingale (resp. submartingale) is a loosing (resp. winning) game.

# Binomial tree: generalization Basic notions on Probability

• If  $M := (M_k)_{1 \le k \le n}$  is a  $\mathcal{F}$ -martingale under  $\mathbb{P}$  then

$$\mathbb{E}^{\mathbb{P}}[M_k|\mathcal{F}_i] = M_i$$
 , for any  $i \leq k$ 

and in particular, we have

$$\mathbb{E}^{\mathbb{P}}[M_k] = M_0.$$

# Binomial tree: generalization Set-up

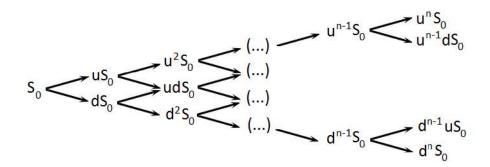
- We extend the model of the previous chapter to *n* periods.
- We consider an interval of time [0, T] divided into n periods:  $0 = t_0 < t_1 < ... < t_n = T$ .
- There are two assets:
  - ▶ A non-risky asset  $S_t^0$ :

$$1 \to (1+r) \to (1+r)^2 \to ... \to (1+r)^n$$

ightharpoonup A *risky asset S<sub>t</sub>* that evolves according to the following Table

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 22 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 24 / 6

# Binomial tree: generalization Set-up



• The order of occurrence of u and d's does not count. So, the tree recombines (e.g.,  $du^2S_0 = udu \ S_0 = u^2dS_0$ ). At time t the asset may then only take t+1 values. (If the order would have count we would have obtained  $2^t$  values.)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

25 / 68

# Binomial tree: generalization Set-up

• At date t Nature selects  $\omega_t \in \{\omega_t^u, \omega_t^d\}$ . So

$$\Omega := \{(\omega_1, \omega_2, ..., \omega_n) | \forall i \in \{0, 1, ..., n\} \text{ we have } \omega_i = \omega_i^u \text{ or } \omega_i = \omega_i^d\}.$$

We assume that the probability of occurrence of *u* is time-invariant:

$$\mathbb{P}\left(\omega_{i}=\omega_{i}^{u}\right)=p$$

and

$$\mathbb{P}\left(\omega_{i}=\omega_{i}^{d}\right)=1-p.$$

# Binomial tree: generalization Set-up

So

$$\mathbb{P}(\omega_1, \omega_2, ..., \omega_n) = p^{\#\{i \in \{0, 1, ..., n\} | \omega_i = \omega_i^u\}} \times (1 - p)^{\#\{i \in \{0, 1, ..., n\} | \omega_i = \omega_i^d\}}.$$

• The value of the asset at time  $t_i$ , can be written as

$$S_{t_i} = S_0 \prod_{k=0}^i Y_k$$

with  $(Y_k)_{k=0,\dots,n}: \Omega^{n+1} \longmapsto \{u,d\}^{n+1}$  being a collection of random variables i.i.d., with  $Y_k$  is realized at time k, and takes the value u with probability p and d with probability (1-p).

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

27 / 6

# Binomial tree: generalization Set-up

So we have

$$\mathbb{P}\left(\mathsf{Y}_{i}=u\right)=\mathbb{P}\left(\omega_{i}=\omega_{i}^{u}\right)=p$$

and

$$\mathbb{P}(Y_i = d) = \mathbb{P}\left(\omega_i = \omega_i^d\right) = 1 - p.$$

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 26 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 28 / 6

# Binomial tree: generalization Set-up

• The information available at time  $t_i$  is given by the filtration  $(\mathcal{F}_{t_k})_{1 \le k \le j}$ , with

$$\mathcal{F}_{t_i} := \sigma(\omega_1, \omega_2, ..., \omega_i) = \sigma(Y_1, Y_2, ..., Y_i) = \sigma(S_{t_1}, S_{t_2}, ..., S_{t_i}).$$

### **Definition (Mathematics)**

In our market, a **derivative** is a random variable that is  $\mathcal{F}_{\mathcal{T}}$ —measurable.

• So, a derivative takes the form of a function  $\phi(S_{t_1}, S_{t_2}, ..., S_{t_i})$ .

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

29 / 68

# Chapter 3: Binomial tree with n period Outline

- 1 Introduction
- 2 Binomial Trees: Two-Step
- 3 Binomial tree: generalization
  - Basic notions on Probability
  - Setup
  - Simple portfolio strategies
  - Arbitrage and risk-neutral probability
  - Hedging derivative
- 4 Conclusion

# Binomial tree: generalization Simple portfolio strategies

#### Definition

A **simple portfolio strategy** consists in an initial amount of cash x and a stochastic process  $\Delta := (\Delta_k)_{0 \le k \le n-1}$  which is  $\mathcal{F}$ -adapted.

We denote this strategy by the pair  $(x, \Delta)$  and its value at date  $t_i$  by  $X_{t_i}^{x,\Delta}$ .

- A simple portfolio strategy consists in using a part of an initial amount of cash x to buy (at the initial date) the risky asset in quantity Δ<sub>0</sub>, and to invest the other part of x in a non-risky asset.
  - ▶ Then at date  $t_i$  we invest into the risky asset in quantity  $\Delta_i$ .
  - ▶ The process is  $\mathcal{F}$ —adapted because the amount of investment at date  $t_i$  is determined using the information available at date  $t_i$ .
  - This simple portfolio strategy is self-financing.

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

31/6

# Binomial tree: generalization Simple portfolio strategies

• Between period  $t_i$  and  $t_{i+1}$ , the portfolio takes the form of  $\Delta_i$  units of risky asset and  $\frac{X_{t_i}^{x,\Delta} - \Delta_i S_{t_i}}{(1+r)^i}$  units of non-risky asset. So, the value of the portfolio at time  $t_i$  is given by

$$X_{t_i}^{\mathsf{X},\Delta} = \Delta_i \mathcal{S}_{t_i} + \frac{X_{t_i}^{\mathsf{X},\Delta} - \Delta_i \mathcal{S}_{t_i}}{\left(1+r\right)^i} \left(1+r\right)^i.$$

• Since the strategy is self-financing, no money is withdrawn nor inserted during the time interval  $[t_i, t_{i+1})$ , so we have

$$X_{\mathbf{t}_{i+1}}^{x,\Delta} = \Delta_i S_{\mathbf{t}_{i+1}} + \frac{X_{t_i}^{x,\Delta} - \Delta_i S_{t_i}}{(1+r)^i} (1+r)^{\mathbf{i}+1}.$$

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 30 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 32 / 68

# Binomial tree: generalization Simple portfolio strategies

- Let  $\tilde{Z}$  denotes the **current value** of the variable Z at date t = 0, 1, ..., n.
  - ▶ So, the current value of the portfolio *X* at date *t<sub>i</sub>* writes as

$$ilde{X}_{t_i}^{\mathbf{x},\Delta} := rac{X_{t_i}^{\mathbf{x},\Delta}}{\left(1+r
ight)^i}$$

and the current value of the risky asset at date t<sub>i</sub> writes as

$$\tilde{\mathsf{S}}_{t_i} := rac{\mathsf{S}_{t_i}}{\left(1+r
ight)^i}.$$

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

33 / 68

# Binomial tree: generalization Simple portfolio strategies

So we have

$$egin{array}{lll} ilde{X}_{t_{i}+1}^{ ilde{x},\Delta} &=& rac{X_{t_{i}+1}^{ ilde{x},\Delta}}{(1+r)^{i+1}} \ &=& rac{\Delta_{i}S_{t_{i+1}} + rac{X_{t_{i}}^{ ilde{x},\Delta} - \Delta_{i}S_{t_{i}}}{(1+r)^{i}} \left(1+r
ight)^{i+1}}{(1+r)^{i+1}} \ &=& \Delta_{i} ilde{S}_{t_{i}+1} + rac{X_{t_{i}}^{ ilde{x},\Delta} - \Delta_{i}S_{t_{i}}}{(1+r)^{i}} \ &=& \Delta_{i} ilde{S}_{t_{i}+1} + \left( ilde{X}_{t_{i}}^{ ilde{x},\Delta} - \Delta_{i} ilde{S}_{t_{i}}
ight). \end{array}$$

## Binomial tree: generalization Simple portfolio strategies

From

$$egin{array}{lll} ilde{X}_{t_i}^{ ilde{x},\Delta} &=& ilde{X}_{t_i}^{ ilde{x},\Delta} + \left(\Delta_i ilde{S}_{t_i} - \Delta_i ilde{S}_{t_i}
ight) \ &=& \Delta_i ilde{S}_{t_i} + \left( ilde{X}_{t_i}^{ ilde{x},\Delta} - \Delta_i ilde{S}_{t_i}
ight) \end{array}$$

we obtain the self-financing condition

$$\tilde{X}_{t_{i+1}}^{x,\Delta} - \tilde{X}_{t_i}^{x,\Delta} = \Delta_i \left( \tilde{S}_{t_{i+1}} - \tilde{S}_{t_i} \right). \tag{1}$$

This condition can be rewritten as

$$\tilde{X}_{t_{i+1}}^{\mathsf{x},\Delta} = \mathsf{x} + \sum_{k=0}^{i} \Delta_k \left( \tilde{\mathsf{S}}_{t_{k+1}} - \tilde{\mathsf{S}}_{t_k} \right).$$

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

35 / 6

# Binomial tree: generalization Arbitrage and risk-neutral probability

#### Definition

A **simple arbitrage** is a simple portfolio strategy that gives to a portfolio no value at time t=0 and a value at time  $T=t_n$  which is strictly positive with positive probability and is never negative. Formally, it is a pair  $(x=0,\Delta)$  with  $\Delta\in\mathbb{R}^n$  such that

$$X_{\mathcal{T}}^{0,\Delta} \geq 0$$
 and  $\mathbb{P}(X_{\mathcal{T}}^{0,\Delta} > 0) > 0$ .

#### Definition

We say that there is no simple arbitrage opportunity (NAO') if

$$\forall \Delta \in \mathbb{R}^n \ \{X_T^{0,\Delta} \geq 0 \implies X_T^{0,\Delta} = 0 \ \mathbb{P} - a.s.\}$$

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 34 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 36 / 6

# Binomial tree: generalization Arbitrage and risk-neutral probability

### Proposition (3.2)

If NAO' then d < 1 + r < u.

#### Proof.

We proceed by contradiction. Assume NAO' and  $d \ge 1 + r$ .

Consider the following simple arbitrage strategy:

- buy one unit of the risky asset; and
- sell the equivalent amount of the non risky asset in period t = 0;
- then resell the unit of the risky asset at time  $t_1$ ; and
- invest it into the non-risky asset until period T
- (i.e., x = 0,  $\Delta_0 = 1$ , and  $\Delta_i = 0$  for any  $i \ge 1$ ). (...)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

37 / 6

# Binomial tree: generalization Arbitrage and risk-neutral probability

### Proof.

Such a strategy is deterministic so it is  $\mathcal{F}$ -adapted. At date  $T = t_n$  the portfolio value is given by:

$$egin{array}{lcl} ilde{X}_{T}^{0,\Delta} &=& 0+\displaystyle\sum_{k=0}^{n-1}\Delta_{k}\left( ilde{S}_{t_{k+1}}- ilde{S}_{t_{k}}
ight) \ &=& ilde{S}_{t_{1}}- ilde{S}_{t_{0}} \end{array}$$

(...)

# Binomial tree: generalization Arbitrage and risk-neutral probability

#### Proof.

Since  $S_{t_1}$  can only takes two values (either  $uS_0$  or  $dS_0$ ), the portfolio value at time T is either

$$(1+r)^n S_0\left(\frac{u}{(1+r)}-1\right)>0$$

or

$$(1+r)^n S_0\left(\frac{d}{(1+r)}-1\right) \geq 0$$

which contradicts NAO', since both values occur with strictly positive probabilities (resp. p and (1 - p)). (...)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

39 / 6

# Binomial tree: generalization Arbitrage and risk-neutral probability

### Proof.

Similarly, we obtain a contradiction by assuming  $u \le 1 + r$  and by considering the simple arbitrage strategy that consists in:

- selling one unit of the risky asset; and
- buying the equivalent amount of the non risky asset in period t = 0;
- I.e., x = 0,  $\Delta_0 = -1$ , and  $\Delta_i = 0$  for any  $i \ge 1$ .

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 38 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 40 / 68

### Binomial tree: generalization Arbitrage and risk-neutral probability

• Consider the following probability on  $\Omega$ :

$$\mathbb{Q}(\omega_1, \omega_2, ..., \omega_n) = q^{\#\{i \in \{1, ..., n\} | \omega_i = \omega_i^u\}} \times (1 - q)^{\#\{i \in \{1, ..., n\} | \omega_i = \omega_i^d\}}$$

with

$$q:=\frac{(1+r)-d}{u-d}.$$

We then have

$$\mathbb{Q}\left(S_{t_{i}}=uS_{t_{i-1}}\right)=\mathbb{Q}\left(Y_{i}=u\right)=q$$

and

$$\mathbb{Q}\left(S_{t_i}=dS_{t_{i-1}}\right)=\mathbb{Q}\left(Y_i=d\right)=1-q.$$

• Let us show that  $\mathbb{O}$  is a risk-neutral probability measure.

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

41 / 68

### Binomial tree: generalization Arbitrage and risk-neutral probability

By definition (see chap. 2), a risk-neutral probability measure or equivalent martingale measure (EMM) is a probability measure 0 which is equivalent to  $\mathbb{P}$  and for which any simple strategy expressed in current value is a martingale.

### Proposition (3.3)

$$\tilde{\mathsf{S}} := \left( \tilde{\mathsf{S}}_{t_i} \right)_{i \in \{1,2,...,n\}}$$
 is a  $\mathcal{F}-$ martingale under  $\mathbb{Q}.$ 

### Proof.

Clearly,  $\tilde{S}_{t_i} := \frac{S_{t_i}}{(1+r)^i}$  is  $\mathcal{F}_{t_i}$ -measurable for each  $i \leq n$ , so  $\tilde{S}$  is  $\mathcal{F}$ -adapted.(...)

### Binomial tree: generalization Arbitrage and risk-neutral probability

#### Proof.

Moreover, we have

$$\mathbb{E}^{\mathbb{Q}}[| ilde{S}_{t_i}|] = rac{\mathbb{E}^{\mathbb{Q}}[|S_{t_i}|]}{\left(1+r
ight)^i} < +\infty, ext{ for any } i \leq n$$

and (...)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Binomial tree: generalization Arbitrage and risk-neutral probability

#### Proof.

$$\mathbb{E}^{\mathbb{Q}}[\tilde{S}_{t_{i+1}}|\mathcal{F}_{t_{i}}] = \frac{qu\tilde{S}_{t_{i}} + (1-q)d\tilde{S}_{t_{i}}}{1+r}$$

$$= \frac{1}{1+r} \left( \frac{(1+r)-d}{u-d} u \tilde{S}_{t_{i}} + \left( 1 - \frac{(1+r)-d}{u-d} \right) d\tilde{S}_{t_{i}} \right)$$

$$= \frac{1}{1+r} \left( \frac{(1+r)-d}{u-d} u + \frac{u-(1+r)}{u-d} d \right) \tilde{S}_{t_{i}}$$

$$= \frac{1}{1+r} \left( \frac{(1+r)(u-d)}{u-d} \right) \tilde{S}_{t_{i}} = \tilde{S}_{t_{i}}.$$

Jérôme MATHIS (LEDa)

# Binomial tree: generalization

Arbitrage and risk-neutral probability

 The following result states that if the current values of the standard assets are martingale under a given probability then it is so of the current value of any simple portfolio strategy.

### Proposition (3.4)

The current value  $\tilde{X}^{x,\Delta}$  of any simple portfolio strategy  $(x,\Delta)$  is a  $\mathcal{F}$ -martingale under  $\mathbb{Q}$ .

#### Proof.

Clearly,  $\tilde{X}^{x,\Delta}$  is  $\mathcal{F}-$ adapted. Moreover, we have

$$\mathbb{E}^{\mathbb{Q}}[|\tilde{X}_{t_i}^{\mathsf{x},\Delta}|]<+\infty$$
, for any  $i\leq n$ .

(...)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

45 / 68

# Binomial tree: generalization Arbitrage and risk-neutral probability

#### Proof.

Now it suffices to show that

$$\mathbb{E}^{\mathbb{Q}}[ ilde{X}_{t_{i+1}}^{x,\Delta}- ilde{X}_{t_i}^{x,\Delta}|\mathcal{F}_{t_i}]=0$$

From (1) we have

$$\mathbb{E}^{\mathbb{Q}}[\tilde{X}_{t_{i+1}}^{\mathsf{x},\Delta} - \tilde{X}_{t_i}^{\mathsf{x},\Delta}|\mathcal{F}_{t_i}] = \mathbb{E}^{\mathbb{Q}}[\Delta_i \left(\tilde{S}_{t_{i+1}} - \tilde{S}_{t_i}\right)|\mathcal{F}_{t_i}]$$

SO

$$\mathbb{E}^{\mathbb{Q}}[\tilde{X}_{t_{i+1}}^{x,\Delta} - \tilde{X}_{t_i}^{x,\Delta}|\mathcal{F}_{t_i}] = \Delta_i \mathbb{E}^{\mathbb{Q}}[\tilde{S}_{t_{i+1}} - \tilde{S}_{t_i}|\mathcal{F}_{t_i}] = 0$$

where the last equality comes from the previous Proposition.

# Binomial tree: generalization Arbitrage and risk-neutral probability

### Theorem (3.5)

If d < R < u then there is an equivalent martingale measure  $\mathbb{Q}$ .

#### Proof.

According to the previous result we know that  $\mathbb Q$  is a probability measure for which any simple strategy expressed in current value is a martingale. Moreover,  $\mathbb Q$  is equivalent to  $\mathbb P$  since d < R < u implies that  $q \in (0,1)$  and that  $\mathbb Q\left(\omega_1,\omega_2,...,\omega_n\right) > 0$  for every  $(\omega_1,\omega_2,...,\omega_n) \in \Omega$ .

The value at date  $t_i$  of any simple portfolio strategy writes as

$$X_{t_i}^{x,\Delta} = rac{\mathbb{E}^{\mathbb{Q}}[X_T^{x,\Delta}|\mathcal{F}_{t_i}]}{(1+r)^{n-i}}.$$

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chanter 3

47 / 6

Binomial tree: generalization Arbitrage and risk-neutral probability

- Hence, if we are able to hedge a derivative, NAO implies that the value of the hedging portfolio at date  $t_i$  is given by the expected current value of its final value under the risk-neutral probability.
- Before exploiting this idea, let us state the following result.

### Proposition (3.6)

If there is an equivalent martingale measure Q then NAO' holds.

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 46 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 48 / 68

### Binomial tree: generalization Arbitrage and risk-neutral probability

#### Proof.

As in the previous chapter, let  $\Delta \in \mathbb{R}^n$  such that  $X_{\tau}^{0,\Delta} \geq 0$ .

Since (1) is an equivalent martingale measure, we have

$$\mathbb{E}^{\mathbb{Q}}\left[X_T^{x=0,\Delta}\right]=x=0.$$

Which means that  $X_T^{0,\Delta}$  is a random variable that is positive and whose expected value is zero.

This variable is then equal to zero  $\mathbb{Q} - a.s.$ 

Finally, since  $\mathbb Q$  is equivalent to  $\mathbb P$  we obtain  $\mathbb P\left(X^{0,\Delta}_{\mathcal T}>0\right)=0.$ 

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Arbitrage&Pricing

### Binomial tree: generalization Arbitrage and risk-neutral probability

• From Proposition 3.2

$$NAO' \Longrightarrow d < R < \mu$$

• From Theorem 3.5

 $d < R < u \Longrightarrow$  there is an equivalent martingale measure

From Proposition 3.6 we have

there is an equivalent martingale measure  $\implies NAO'$ 

## Binomial tree: generalization Arbitrage and risk-neutral probability

Hence we obtain

$$NAO' \iff d < R < u$$

⇔ there is an equivalent martingale measure.

Saying that

"the current values of every standard asset is martingale under Q" is then equivalent to say that

"the current value of every simple portfolio strategy is martingale under Q".

Jérôme MATHIS (LEDa)

### Chapter 3: Binomial tree with n period Outline



- Binomial tree: generalization
  - Basic notions on Probability
  - Setup
  - Simple portfolio strategies
  - Arbitrage and risk-neutral probability
  - Hedging derivative

Jérôme MATHIS (LEDa) Chapter 3 Jérôme MATHIS (LEDa) Arbitrage&Pricing Arbitrage&Pricing

## Binomial tree: generalization Hedging derivative

### Theorem (3.7)

In our market, every derivative is replicable by using a simple portfolio strategy  $(x, \Delta)$ .

#### Question

What is the form of  $(x, \Delta)$ ?

• We are looking at for a simple portfolio strategy  $(x, \Delta)$  replicating a derivative of value  $C_T$  at date T. Since  $C_T$  is  $\mathcal{F}_{t_n}$ -adapted, the value of the derivative takes the form of a function  $\phi(S_{t_1}, S_{t_2}, ..., S_{t_n})$ so  $(x, \Delta)$  has to satisfy

$$X_{t_n}^{\mathsf{x},\Delta} = \phi\left(\mathsf{S}_{t_1},\mathsf{S}_{t_2},...,\mathsf{S}_{t_n}\right)$$

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

53 / 68

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

# Binomial tree: generalization Hedging derivative

• According to Proposition 3.4, the current value of every simple portfolio strategy is martingale under the EMM  $\mathbb{Q}$ , so the value  $X_t^{x,\Delta}$ of the replicating portfolio at date  $t_k$  satisfies

$$X_{t_k}^{\mathsf{x},\Delta} = \frac{\mathbb{E}^{\mathbb{Q}}\left[X_{t_n}^{\mathsf{x},\Delta}|\mathcal{F}_{t_k}\right]}{(1+r)^{n-k}} = \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_1},S_{t_2},...,S_{t_n}\right)|\mathcal{F}_{t_k}\right]}{(1+r)^{n-k}}.$$

So the initial amount of our replicating portfolio has to be

$$x := \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{n}}\right)\right]}{(1+r)^{n}}.$$
 (2)

## Binomial tree: generalization Hedging derivative

• Now, since  $\frac{1}{(1+r)^{n-k}}\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_1},S_{t_2},...,S_{t_n}\right)|\mathcal{F}_{t_k}\right]$  is a random variable which is  $\mathcal{F}_{t_k}$  –measurable it can be rewritten as a function  $V_k(S_{t_1}, S_{t_2}, ..., S_{t_k})$  where  $V_k(\cdot)$  is deterministic. Let

$$V_{k}\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{k}}\right) := \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{n}}\right) | \mathcal{F}_{t_{k}}\right]}{(1+r)^{n-k}}.$$
 (3)

• In the previous chapter which introduces the model with one period, we have seen that the quantity of the risky asset  $\Delta$  of the replicating portfolio looks like the variation of the value of the derivative induced by the variation of the underlying asset.

### Hedging derivative

• In the proof of Theorem, we shall take  $\Delta := (\Delta)_{k \in \{1,2,\dots,n\}}$  satisfying that for any  $k \in \{1, 2, ..., n\}$ 

$$\Delta_{k} := \frac{V_{k+1}\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{k}}, uS_{t_{k}}\right) - V_{k+1}\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{k}}, dS_{t_{k}}\right)}{uS_{t_{k}} - dS_{t_{k}}}.$$
(4)

- Observe that for any  $k \in \{1, 2, ..., n\}$ ,  $\Delta_k$  is  $\mathcal{F}_{t_k}$ —measurable as a function of  $(S_{t_1}, S_{t_2}, ..., S_{t_k})$ . So,  $\Delta$  is  $\mathcal{F}$ -adapted and  $(x, \Delta)$  is indeed a simple portfolio strategy.
- Now, let us establish the proof of Theorem 3.7 according to which the simple portfolio strategy  $(x, \Delta)$  with  $\Delta$  satisfying (4) replicates our derivative.

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 54 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing

# Binomial tree: generalization Hedging derivative

### Proof.

We have to show that

$$X_{t_n}^{x,\Delta} = \phi(S_{t_1}, S_{t_2}, ..., S_{t_n}) = V_n(S_{t_1}, ..., S_{t_n}).$$

Let us proceed by induction. Let P(k),  $k \in \{1, 2, ..., n\}$  be the following statement:

$$X_{t_k}^{x,\Delta} = V_k\left(S_{t_1},...,S_{t_k}\right)$$

Clearly, P(0) is true. Indeed, we have  $X_{t_0}^{x,\Delta}=x$  and by (2)

$$x := \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{n}}\right)\right]}{(1+r)^{n}} = \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_{1}}, S_{t_{2}}, ..., S_{t_{n}}\right) | \mathcal{F}_{t_{0}}\right]}{(1+r)^{n-0}}$$

which by (3) correspond to  $V_0(S_{t_0})$ . (...)

Jérôme MATHIS (LEDa)

Arbitrage&Pricin

Chapter 3

# Binomial tree: generalization Hedging derivative

#### Proof.

Assume P(k) is true. Let us show that P(k + 1) is true. P(k) writes as

$$X_{t_{k}}^{\mathsf{x},\Delta} = V_{k}(S_{t_{1}},...,S_{t_{k}})$$

$$= \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_{1}},S_{t_{2}},...,S_{t_{n}}\right)|\mathcal{F}_{t_{k}}\right]}{(1+r)^{n-k}}$$

$$= \frac{1}{(1+r)} \frac{\mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_{1}},S_{t_{2}},...,S_{t_{n}}\right)|\mathcal{F}_{t_{k}}\right]}{(1+r)^{n-k-1}}$$

$$= \frac{1}{(1+r)} \mathbb{E}^{\mathbb{Q}}\left[\frac{\phi\left(S_{t_{1}},S_{t_{2}},...,S_{t_{n}}\right)}{(1+r)^{n-(k+1)}}\middle|\mathcal{F}_{t_{k}}\right].$$

# Binomial tree: generalization Hedging derivative

#### Proof.

Now using that for any martingale Z that is  $\mathcal{F}$ —measurable we have for any k and s such that k + s < n

$$\mathbb{E}\left[Z_{t_n}|\mathcal{F}_{t_k}\right] = \mathbb{E}\left[\mathbb{E}\left[Z_{t_n}|\mathcal{F}_{t_{k+s}}\right]|\mathcal{F}_{t_k}\right]$$

we obtain

$$X_{t_k}^{X,\Delta} = \frac{1}{(1+r)} \mathbb{E}^{\mathbb{Q}} \left[ \mathbb{E}^{\mathbb{Q}} \left[ \frac{\phi(S_{t_1}, S_{t_2}, ..., S_{t_n})}{(1+r)^{n-(k+1)}} \middle| \mathcal{F}_{t_{k+1}} \right] \middle| \mathcal{F}_{t_k} \right]$$
$$= \frac{1}{(1+r)} \mathbb{E}^{\mathbb{Q}} \left[ V_{k+1} \left( S_{t_1}, ..., S_{t_{k+1}} \right) \middle| \mathcal{F}_{t_k} \right].$$

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

er 3 59

Binomial tree: generalization Hedging derivative

#### Proof.

So,

(...)

$$X_{t_{k}}^{\mathsf{X},\Delta} = \frac{\mathbb{E}^{\mathbb{Q}} \left[ \begin{array}{c} V_{k+1} \left( S_{t_{1}}, ..., S_{t_{k}}, u \, \mathbf{S}_{t_{k}} \right) \mathbf{1}_{\left\{ Y_{t_{k+1}} = u \right\}} \\ + V_{k+1} \left( S_{t_{1}}, ..., S_{t_{k}}, d \, \mathbf{S}_{t_{k}} \right) \mathbf{1}_{\left\{ Y_{t_{k+1}} = d \right\}} \end{array} \right| \mathcal{F}_{t_{k}} \right]}{\left( 1 + r \right)} \\ = \frac{\mathbb{Q} \left( Y_{t_{k+1}} = u \right) V_{k+1} \left( S_{t_{1}}, ..., S_{t_{k}}, u \, \mathbf{S}_{t_{k}} \right) \\ + \mathbb{Q} \left( Y_{t_{k+1}} = d \right) V_{k+1} \left( S_{t_{1}}, ..., S_{t_{k}}, d \, \mathbf{S}_{t_{k}} \right)}{\left( 1 + r \right)}$$

# Binomial tree: generalization Hedging derivative

#### Proof.

That is

$$X_{t_{k}}^{X,\Delta} = \frac{\left[qV_{k+1}\left(S_{t_{1}},...,S_{t_{k}},uS_{t_{k}}\right) + (1-q)V_{k+1}\left(S_{t_{1}},...,S_{t_{k}},dS_{t_{k}}\right)\right]}{(1+r)}$$
(5)

Now, from (1) we have

$$ilde{X}_{t_{k+1}}^{x,\Delta} = ilde{X}_{t_k}^{x,\Delta} + \Delta_k \left( ilde{S}_{t_{k+1}} - ilde{S}_{t_k} \right)$$

so

(...)

$$\frac{X_{t_{k+1}}^{x,\Delta}}{(1+r)^{k+1}} = \frac{X_{t_k}^{x,\Delta}}{(1+r)^k} + \Delta_k \left( \frac{S_{t_{k+1}}}{(1+r)^{k+1}} - \frac{S_{t_k}}{(1+r)^k} \right)$$

Jérôme MATHIS (LEDa

Arbitrage&Pricing

Chapter 3

# Binomial tree: generalization Hedging derivative

#### Proof.

which rewrites as

$$X_{t_{k+1}}^{\mathsf{X},\Delta} = X_{t_k}^{\mathsf{X},\Delta} \left( 1 + r \right) + \Delta_k \left( S_{t_{k+1}} - \left( 1 + r \right) S_{t_k} \right)$$

Using (5) and (4) we obtain

$$X_{t_{k+1}}^{x,\Delta} = qV_{k+1}(S_{t_1},...,S_{t_k},uS_{t_k}) + (1-q)V_{k+1}(S_{t_1},...,S_{t_k},dS_{t_k}) + \frac{V_{k+1}(S_{t_1},S_{t_2},...,S_{t_k},uS_{t_k}) - V_{k+1}(S_{t_1},S_{t_2},...,S_{t_k},dS_{t_k})}{uS_{t_k} - dS_{t_k}} \times (S_{t_{k+1}} - (1+r)S_{t_k}).$$
(...)

# Binomial tree: generalization Hedging derivative

#### Proof.

By replacing  $S_{t_{k+1}}$  with  $Y_{k+1}S_{t_k}$  and q with  $\frac{1+r-d}{u-d}$  we have

$$X_{t_{k+1}}^{x,\Delta} = V_{k+1}(S_{t_1},...,S_{t_k},uS_{t_k})\frac{Y_{k+1}-d}{u-d} + V_{k+1}(S_{t_1},...,S_{t_k},dS_{t_k})\frac{u-Y_{k+1}}{u-d}.$$

Since  $Y_{k+1}$  can only takes the value u and d we obtain

$$X_{t_{k+1}}^{x,\Delta} = V_{k+1}\left(S_{t_1},...,S_{t_k},Y_{k+1}S_{t_k}\right) = V_{k+1}\left(S_{t_1},...,S_{t_k},S_{t_{k+1}}\right)$$

which is P(k + 1). (...)

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

63 / 6

# Binomial tree: generalization Hedging derivative

#### Proof.

Since every derivative is replicable, under NAO, a derivative of final value

$$C_{\mathcal{T}} = \phi\left(S_{t_1}, S_{t_2}, ..., S_{t_n}\right)$$

has a value at date  $t_k$  given by

$$C_{t_k} = rac{1}{\left(1+r
ight)^{n-k}} \mathbb{E}^{\mathbb{Q}}\left[\phi\left(S_{t_1}, S_{t_2}, ..., S_{t_n}
ight) | \mathcal{F}_{t_k}
ight]$$

and in particular at date 0

$$C_0 = \frac{1}{\left(1+r\right)^n} \mathbb{E}^{\mathbb{Q}} \left[\phi\left(S_{t_1}, S_{t_2}, ..., S_{t_n}\right)\right].$$

Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 3 62 / 68 Jérôme MATHIS (LEDa) Arbitrage&Pricing Chapter 5

# Binomial tree: generalization Hedging derivative

- It means that the derivative price at any date can be obtained by backward induction.
  - we can treat each binomial step separately and work back from the end of the life of the option to the beginning to obtain the current value of the option.
- The following result extends Proposition 2.6 of Chapter 2 to our setup.

### Proposition (3.8)

If every asset is replicable with a simple portfolio strategy (complete market) then the equivalent martingale measure is unique.

#### Proof.

The proof is the one of Proposition 2.6.

65 / 68

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

# Chapter 3: Binomial tree with n period Outline

- Introduction
- Binomial Trees: Two-Step
- Binomial tree: generalization
- 4 Conclusion

### Conclusion

- The binomial model with *n* periods produces similar results to the model with one period:
  - ▶ the derivative price does not depend the probabilities of up, p, and down, (1 p), movements in the stock price at each node of the tree.
  - ▶ the derivative price is the expected current value, expressed with the equivalent martingale measure ℚ, of its future value.
  - ► the quantity ∆ of the risky asset in the replicative portfolio measures how the derivative price moves with the underlying asset price.
- When stock price movements are governed by a multistep binomial tree, we can use backward induction to deduce the initial option price from the final option price.

Jérôme MATHIS (LEDa)

Arbitrage&Pricing

Chapter 3

67 1 60

### Conclusion

- We can assume the world is risk-neutral when valuing an option.
  - ► No-arbitrage arguments and risk-neutral valuation are equivalent and lead to the same option prices.
- The delta of a stock option,  $\Delta$ , considers the effect of a small change in the underlying stock price on the change in the option price.
  - ▶ It is the ratio of the change in the option price to the change in the stock price.
  - For a riskless position, an investor should buy  $\Delta$  shares for each option sold.
  - ► An inspection of a typical binomial tree shows that delta changes during the life of an option.
  - ► This means that to hedge a particular option position, we must change our holding in the underlying stock periodically.

 Jérôme MATHIS (LEDa)
 Arbitrage&Pricing
 Chapter 3
 66 / 68
 Jérôme MATHIS (LEDa)
 Arbitrage&Pricing
 Chapter 3
 68 / 6