

# Financial Derivatives

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# Preliminary requirements

- ▶ Please email TODAY your CV with passport-like photo at

[merella@unica.it](mailto:merella@unica.it)

- ▶ In the email text, rate your knowledge of the following topics

[1-10, 1 = awful, 10 = excellent]

- ▶ mathematics (calculus)
- ▶ statistics and econometrics
- ▶ computational methods

# Preliminary information

- ▶ Course material

[unica.it/unica/page/it/financial\\_derivatives\\_and\\_risk\\_management](https://unica.it/unica/page/it/financial_derivatives_and_risk_management)

- ▶ Office hours

Fridays, 11-12, [meet.google.com/imo-jxka-qvn](https://meet.google.com/imo-jxka-qvn)

- ▶ please email me in advance

# Examination format

- ▶ The exam features 12 on-screen written questions, answered orally
- ▶ The questions are divided in 4 groups, each covering a different topic
  - ▶ the 3 questions in each group are in an increasing order of difficulty
  - ▶ each question yield up to three points
    - ▶ you can still score 27/30 by failing to reply to one whole topic!
    - ▶ and still 24/30 by failing to reply to the most difficult questions!
- ▶ The duration of the exam is 12 minutes per candidate
  - ▶ this gives you one minute per question on average
  - ▶ practising the course exercise is of paramount importance!
- ▶ A mock exam will be provided at the end of week 5

# Objective

- ▶ The market of *financial derivatives* is huge

[en.wikipedia.org/wiki/Derivative\\_\(finance\)](https://en.wikipedia.org/wiki/Derivative_(finance))

- ▶ its value is about \$640T when measured in terms of underlying assets
  - ▶ more than four times as large as the world GDP (\$142T)
  - ▶ more than ten times as large as the value of stock traded (\$60T)
- ▶ The reason is that derivatives play a key role in transferring a wide range of risks in the economy from one entity to another
- ▶ Derivatives have become so important that who works in finance *needs* to understand how they work, are used and priced
- ▶ Our goal is to try and understand exactly that!

# Paradigm

- ▶ One simple question conveys the key issue of financial economics

## what is the price of financial risk?

- ▶ In asset pricing, we take a macroeconomic stance and find that the price of systematic risk is ultimately unknown
  - ▶ quantifying and pricing risk would help avoiding financial crises, but...
  - ▶ we see the failure of *absolute pricing* models (CAPM, CCAPM, ...)
  - ▶ we observe the inconsistency of *relative pricing* models (APT, ...)
- ▶ In risk management, we study the microeconomic perspective and show that the price of risk for specific asset can be identified
  - ▶ macroeconomic inconsistency of relative pricing is due to the failure of identifying the reference asset (market portfolio composition)
  - ▶ from a microeconomic point of view, the reference asset is perfectly identified for financial derivatives: it is the **underlying asset**
  - ▶ hence we can manage individual investors' exposure to financial risk

# Approach

- ▶ We conceive risk as an *opportunity cost*

[en.wikipedia.org/wiki/Opportunity\\_cost](https://en.wikipedia.org/wiki/Opportunity_cost)

- ▶ If my capital is invested in bonds, the risk (opportunity cost) is the inability to devote those resources to a more profitable investment
- ▶ If my capital is invested in a more profitable investment, that might (in fact, *must*) come at the risk (opportunity cost) of making losses
- ▶ If I have a *short position* in an investment, I face the exactly opposite risk (opportunity cost)
  - ▶ things may go too well (for the investment in question)
  - ▶ I may have to pay a lot of money to close my position

[en.wikipedia.org/wiki/Short\\_\(finance\)](https://en.wikipedia.org/wiki/Short_(finance))

# Preview of findings

- ▶ We show that derivatives can *completely* offset financial risk
- ▶ We also show that derivatives can be *exactly* priced
- ▶ We develop out intuitions and the resulting model in discrete time but we also lay the foundations for continuous-time pricing
- ▶ Our applications focus on **options**, by far the most interesting nontrivial type of derivative

[en.wikipedia.org/wiki/Option\\_\(finance\)](https://en.wikipedia.org/wiki/Option_(finance))

- ▶ We study classical hedging strategies based on the so-called **Greeks**

[en.wikipedia.org/wiki/Greeks\\_\(finance\)](https://en.wikipedia.org/wiki/Greeks_(finance))

# Overview

- ▶ Week 1: Basic risk management strategies
- ▶ Week 2: Binomial model
- ▶ Week 3: Multiperiod binomial model
- ▶ Week 4: Discrete-time options
- ▶ Week 5: Classical hedging strategies
- ▶ Week 6: Continuous-time options

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## **1. Basic risk management strategies**

2. Binomial model
3. Multiperiod binomial model
4. Discrete-time options
5. Classical hedging strategies
6. Continuous-time options

# Financial risk management

- ▶ We begin by studying a typical example of opportunity cost handling
  - ▶ consider a stock, for instance Intel Corporation

[finance.yahoo.com/quote/INTC](http://finance.yahoo.com/quote/INTC)

- ▶ suppose that we have a *long position* (we own the stock)

[en.wikipedia.org/wiki/Long\\_\(finance\)](http://en.wikipedia.org/wiki/Long_(finance))

- ▶ The risk is measured by the opportunity cost of keeping our capital invested in the stock we own
- ▶ In turn, the opportunity cost equals the cash flow that obtains by immediately dismissing the stock
- ▶ We assess financial strategies by comparing *potential revenues* and opportunity cost

# Strategy 0: sell the stock

[en.wikipedia.org/wiki/Spot\\_date](https://en.wikipedia.org/wiki/Spot_date)

- ▶ The most elemental strategy is to dismiss the stock immediately
  - ▶ we may store the revenue in the bank, yielding interest at the rate  $R$
  - ▶ if  $R = 0$ , the revenue exactly equals the opportunity cost
  - ▶ the *potential* profit is, quite obviously, *deterministically* null
- ▶ Imagine to stick to the asset under consideration in isolation
- ▶ We have an alternative option: keep the stock in our portfolio for some time (say 6 months)
- ▶ Comparatively, what is the best strategy?
  - ▶ the answer is straightforward: we don't know!
  - ▶ to see this, let's compare profit opportunities between the strategy **buy-and-hold** and the (zero-profit!) strategy **spot-sale**

# Strategy 1: hold the stock

- ▶ If we hold the stock, we need to simulate the future stock value in order to assess our profit opportunities
  - ▶ the cash flow obtains at a future date, so it should be discounted
  - ▶ for simplicity, also here we assume that the discount rate is  $R = 0$
- ▶ We use MATLAB codes designed to forecast daily stock prices
- ▶ The code is simple and requires only a few data on our stock, namely **spot** (current) **price**, (annual) **trend** and (annual) **volatility**
- ▶ We easily obtain these values online, for instance once again at

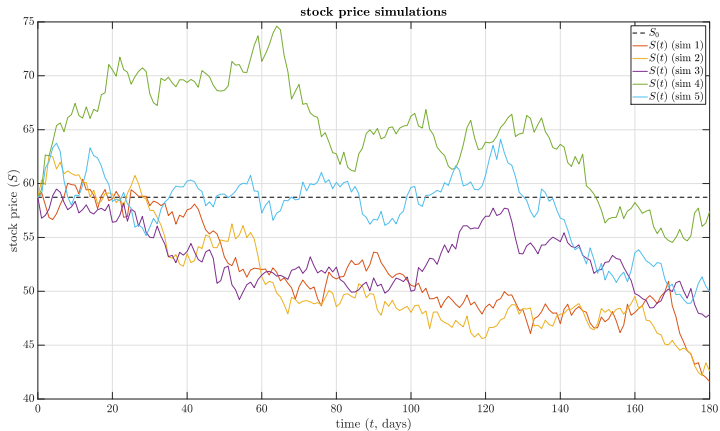
[finance.yahoo.com/quote/INTC](http://finance.yahoo.com/quote/INTC)

- ▶ we click on the 'chart' tab, select '1Y', then 'Historical Volatility' from the 'indicators' menu
- ▶ we take note of current price, price a year ago and volatility and add this information to the MATLAB codes

# Strategy 1: hold the stock

Possible evolution of the stock price

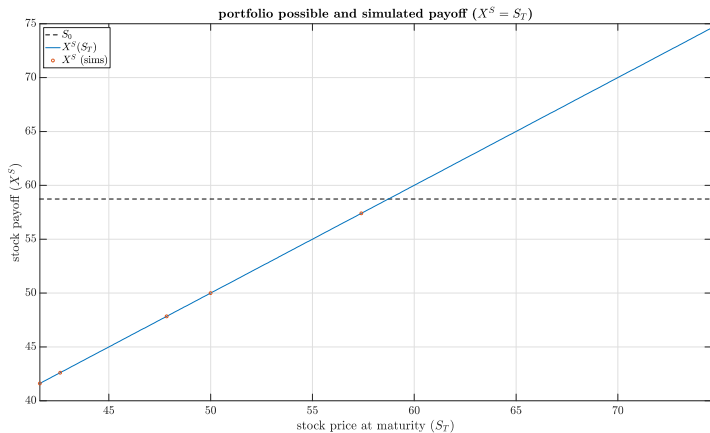
- ▶ MATLAB code: `AE_GraphStockSim.m`



# Strategy 1: hold the stock

Possible payoff (revenue) when holding the stock at maturity

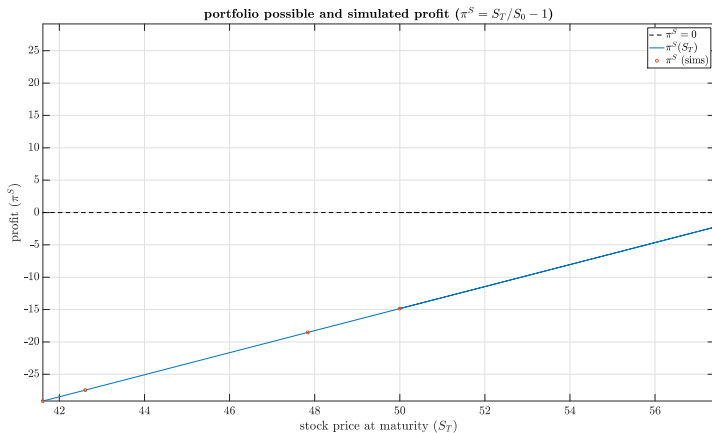
- ▶ MATLAB code: `AE_GraphStockPayoff.m`



# Strategy 1: hold the stock

Possible profit when holding the stock at maturity

- ▶ MATLAB code: `AE_GraphStockProfit.m`



## Strategy 2: add a long European put option

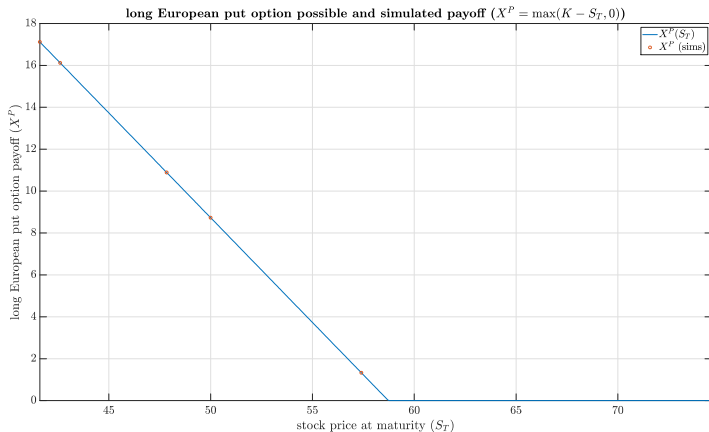
- ▶ From our simulations, we learn that relatively heavy losses could result from holding the stock
- ▶ So it would seem that dismissing the stock today is our best option
- ▶ Yet, is that really so?
  - ▶ we have only made a few simulations, can we trust them?
  - ▶ we have only used to one asset in isolation, what about adding some?
- ▶ There is another possibility: buy a European put option

[en.wikipedia.org/wiki/Put\\_option](https://en.wikipedia.org/wiki/Put_option)

# Strategy 2: add a long a European put option

Possible payoff of the option at maturity

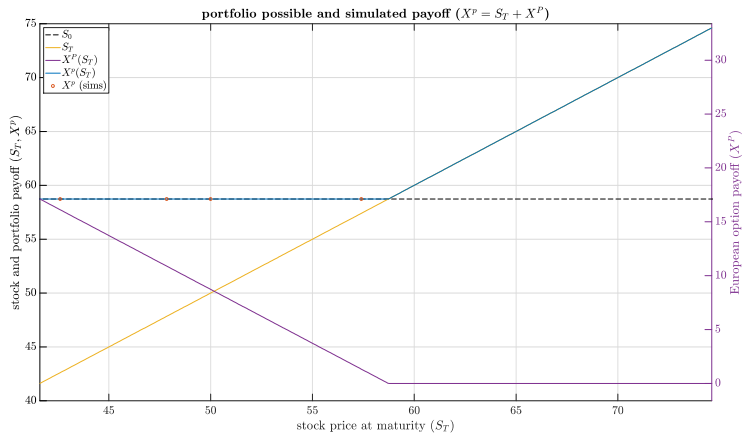
- ▶ MATLAB code: `AE_GraphEurPutPayoff.m`



# Strategy 2: add a long a European put option

Possible payoff of the portfolio (stock,option) at maturity

- ▶ MATLAB code: AE\_GraphPortfolioPayoff.m



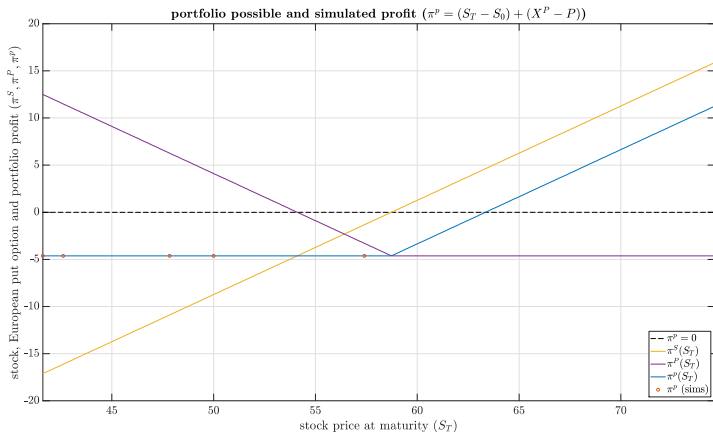
## Strategy 2: add a long a European put option

- ▶ From our analysis we learn that the payoff structure of the option
  - ▶ is positive and complements the revenue structure of the stock when  $S_T \leq K$ , so  $X^P = 0$  (left-hand side of the graph)
  - ▶ equals zero otherwise, so  $X^P > 0$  (right-hand side of the graph)
- ▶ The payoff structure change dramatically when compared to Strategy 1
  - ▶ there are no more losses due to stock price fall
  - ▶ therefore, only gains are allowed
- ▶ Why would anyone take on those potential losses?
  - ▶ the **option price** is the *reward* for the counterpart taking on those potential losses
  - ▶ it is the price of (that part of) risk!

# Strategy 2: add a long a European put option

Possible profit of the portfolio (stock,option) at maturity

- ▶ MATLAB code: AE\_GraphPortfolioProfit.m



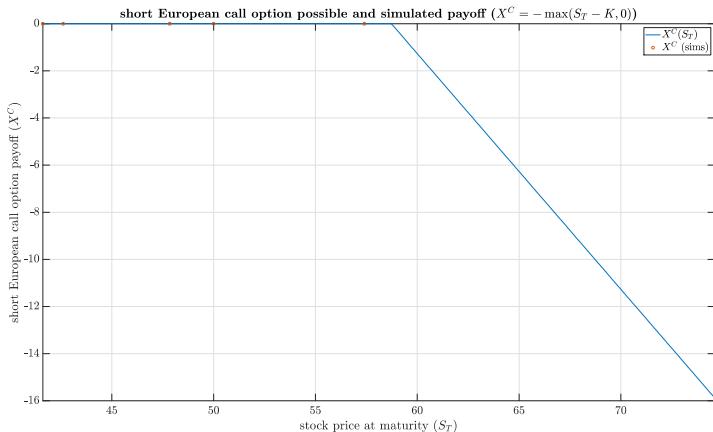
## Strategy 3: add a short European call option

- ▶ In our scenario, the put option price  $P$  evaluates the downward risk
- ▶ But risk stems from any uncertain value (also positive ones!)
- ▶ To obtain the (overall) price of risk, we can use the following logic:
  - ▶ we wish to synthesize a portfolio payoff that is exactly *deterministic*
  - ▶ this way, the cost we pay to implement this strategy measures the price of the entire risk that we are trading on the market
- ▶ In order to do so, we need to
  - ▶ buy a put option (neutralizing the potentially negative payoff of a low stock price at maturity)
  - ▶ *sell* a **call option** (neutralizing the potentially positive payoff of a high stock price at maturity)

# Strategy 3: add a short European call option

Possible payoff of the option at maturity

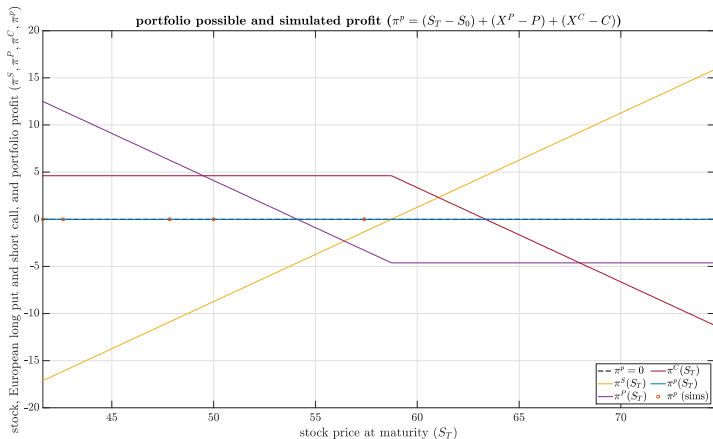
- ▶ MATLAB code: `AE_GraphEurCallPayoff.m`



# Strategy 3: add a short European call option

Possible profit of the portfolio (stock, long put, short call) at maturity

- ▶ MATLAB code: AE\_GraphPortfolio2Profit.m



## Strategy 3: add a short European call option

- ▶ Neutralizing “positive” and “negative” risk we obtain Strategy 0
  - ▶ the portfolio with a short European call and long stock and European put has the same profit as a bank deposit
  - ▶ by definition, the bank’s interest rate is zero
  - ▶ as a result, the profit is deterministically *null*!
- ▶ This concept is known as the **law of one price**

[en.wikipedia.org/wiki/Law\\_of\\_one\\_price](https://en.wikipedia.org/wiki/Law_of_one_price)

- ▶ More generally, this logic follows the **arbitrage-free** principle

[en.wikipedia.org/wiki/Arbitrage](https://en.wikipedia.org/wiki/Arbitrage)

# Understanding financial strategies

- ▶ Consider again the portfolio given in Strategy 2 above
- ▶ We now wish to use this strategy to understand how we can analyze a given financial portfolio
- ▶ This is a critical task to assess a financial position
- ▶ We pose ourselves a number of questions, which will drive the analysis of the main aspects our financial strategies

# Market outlook

- ▶ What belief regarding the evolution of the underlying asset can we infer by observing the portfolio composition?
- ▶ The answer is: *cautiously bullish*
  - ▶ *bullish*: optimistic on the future price evolution of the underlying
    - ▶ the stock price will stay well above the strike price
    - ▶ for this reason, we wish to have a long position in the stock
  - ▶ *cautiously*: although optimistic, the position is also prudent
    - ▶ risk arising from potential falls in the stock price kept to a minimum
    - ▶ hence the long position in a European put option

# Market outlook

- ▶ In fact, the portfolio is a **synthetic call**

[en.wikipedia.org/wiki/Synthetic\\_position](https://en.wikipedia.org/wiki/Synthetic_position)

- ▶ an investor may hold it to receive the benefits of stock ownership
- ▶ insurance policy that protects against depreciation in the stock price
- ▶ The degree of optimism also matters
  - ▶ the more bullish the view, the further **out-of-the-money** we can buy the option in order to create maximum leverage

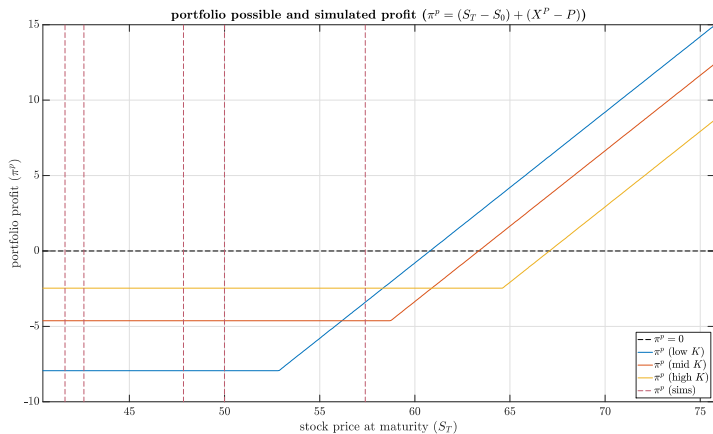
[en.wikipedia.org/wiki/Moneyness](https://en.wikipedia.org/wiki/Moneyness)

- ▶ the more unlikely one believes a fall in the stock price will be, the lower one can choose the strike price
  - ▶ the *net* profit will increase (*in absolute value*) at both ends of the potential stock price distribution
  - ▶ the initial cost of the portfolio will fall: hence the rising leverage

# Market outlook

Possible portfolio profits for different strike prices

- ▶ MATLAB code: AE\_GraphPortfolioProfitK.m



# Market outlook

- ▶ Both larger losses and larger profits obtains with a lower  $K$ 
  - ▶  $P$  declines, boosting the potential  $\pi^P$  when  $S_T$  is sufficiently high
  - ▶ but what is cashed in  $(K - S_T)$  lowers when the option is exercised, thereby increasing the potential loss
- ▶ A few other features of Strategy 2 emerge
  - ▶  $\pi^P$  increases, boundlessly, as  $S_T$  rises
  - ▶ the break-even point obtains when  $S_t$  equals the sum of  $P$  and  $S_0$ 
    - ▶ as a result, it moves rightward as  $K$  increases, rising with  $P$
  - ▶ the maximum loss is the sum between  $P$  and  $S_T - S_0$ 
    - ▶ the higher  $K$ , the larger the first component and the smaller the second: the net result is, anyway, a lower loss

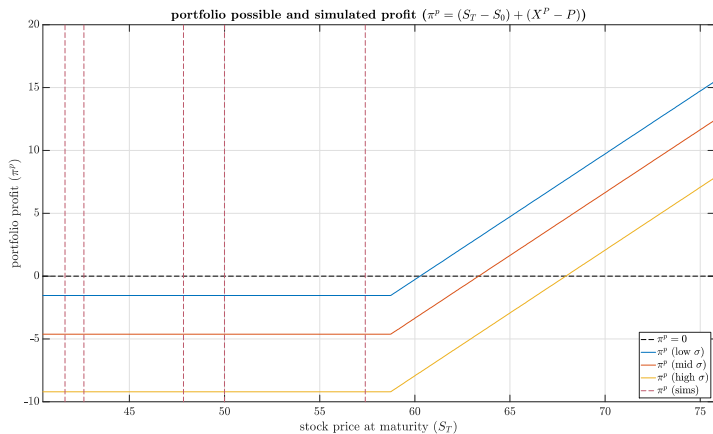
# Volatility

- ▶ What is the performance of our portfolio at maturity when the evolution of the stock is more uncertain?
- ▶ The answer is: profit lowers at all levels of  $S_T$
- ▶ The option value, in fact, increases with volatility
  - ▶ higher volatility raises the probability of a sharp fall in the stock price
  - ▶ in turn, the probability that the option is in the money increases
  - ▶ the initial cost grows without changing the structure of the payoff
  - ▶ hence the uniform fall in the portfolio profitability
- ▶ Expected profit, however, does not necessarily decline, since higher volatility also raises the probability of a sharp *rise* in  $S_T$

# Volatility

Possible portfolio profits for different stock prices variabilities

- ▶ MATLAB code: AE\_GraphPortfolioProfitSigma.m



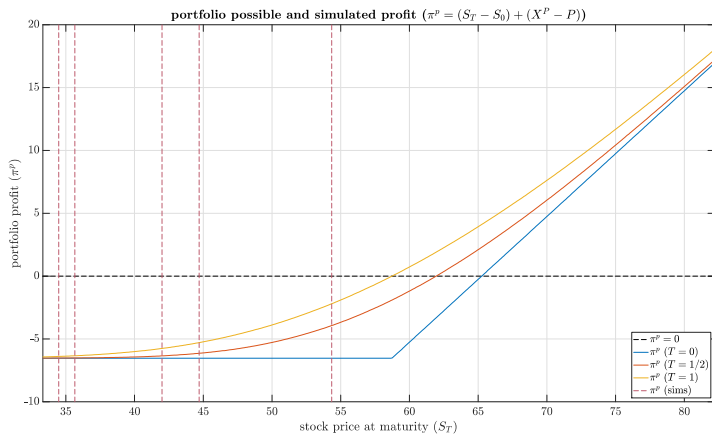
# Time decay

- ▶ What is the price evolution of our portfolio as time passes?
- ▶ The answer is: the value of the portfolio declines over time
  - ▶ the likelihood that  $S_T$  will move away from the value at present falls
  - ▶ in the range of  $S_T$  where the option is in the money, it approaches  $K$
  - ▶ otherwise, it approaches  $S_T$  itself
- ▶ Why from above?
  - ▶ higher  $T$  raises the likelihood of larger strike price movements
  - ▶ portfolio value is lower-bounded by  $K$  but unboundedly raise with  $S_T$
  - ▶ so, in probability, the portfolio value is always larger before maturity
- ▶ To see this, we must analyze the portfolio profit as  $t$  approaches  $T$

# Time decay

Possible portfolio profits at different maturities

- ▶ MATLAB code: AE\_GraphPortfolioProfitT.m



# Option-based financial strategies

[en.wikipedia.org/wiki/Options\\_strategy](https://en.wikipedia.org/wiki/Options_strategy)

- ▶ Risk management often relies on options, due to their versatility
- ▶ It is thus important to familiarize with the leading available strategies

**Exercise** Analyze the following financial strategies

1. Butterfly [en.wikipedia.org/wiki/Butterfly\\_\(options\)](https://en.wikipedia.org/wiki/Butterfly_(options))
2. Straddle [en.wikipedia.org/wiki/Straddle](https://en.wikipedia.org/wiki/Straddle)
3. Strangle [en.wikipedia.org/wiki/Strangle\\_\(options\)](https://en.wikipedia.org/wiki/Strangle_(options))
4. Collar [en.wikipedia.org/wiki/Collar\\_\(finance\)](https://en.wikipedia.org/wiki/Collar_(finance))
5. Fence [en.wikipedia.org/wiki/Fence\\_\(finance\)](https://en.wikipedia.org/wiki/Fence_(finance))

# Theoretical take-away

- ▶ We price risk by using derivatives on a given asset
- ▶ Our benchmark is the price of *that* asset
- ▶ We therefore price the risk of that asset, not the systematic risk
  - ▶ recall the notion of relative pricing: this is a primary example of that
  - ▶ we are *not* identifying the stochastic discount factor!
- ▶ The reason why risk is priced correctly stems from the fact that the “market” composed by the asset and the derivative is *complete*
  - ▶ our line of reasoning can be extended to a finite number of “markets”
  - ▶ however, it cannot be extended to the entire universe of assets
    - ▶ we do not have knowledge of all possible assets (recall the discussion over APT last year)
    - ▶ hence, we fail in correctly identifying the market portfolio

# Theoretical take-away

- ▶ In micro terms, the interesting part is that we can partition the risk of a given position, and price those risk segments separately
  - ▶ this is the role played by financial derivatives
  - ▶ that is why it is so important to be able to price them!
- ▶ Our goal is therefore twofold
  - ▶ we need to master strategies to manage financial risk
  - ▶ we need to price complex derivatives, even those for which we do not have an exact pricing formula

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1. Basic risk management strategies
- 2. Binomial model**
3. Multiperiod binomial model
4. Discrete-time options
5. Classical hedging strategies
6. Continuous-time options

# Introduction

- ▶ We develop a simple model to price any financial derivative
  - ▶ the model building block is the **no-arbitrage condition**

[en.wikipedia.org/wiki/Arbitrage](https://en.wikipedia.org/wiki/Arbitrage)

- ▶ **risk-neutral probabilities** stem from this condition
  - ▶ we use these probabilities to build a **risk-neutral valuation formula**
- ▶ The one-period two-asset structure of the model comprises
  - ▶ two dates,  $t = 0$  (current) and  $t = 1$  (future)
  - ▶ a risk-free asset (**bond**), with price  $B_t$  at time  $t$
  - ▶ a risky asset (**stock**), with price  $S_t$  at time  $t$

[we refer to a stock for simplicity, but the risky asset category spans virtually every financial instrument]

# Bond

- ▶ The **price process**  $B$  is

$$B_0 = 1$$

$$B_1 = 1 + R$$

- ▶  $R$  is the (known) deterministic return rate between  $t = 0$  and  $t = 1$
- ▶ The bond can be interpreted as a bank deposit with **interest rate**  $R$

# Stock

- ▶ The **price process**  $S$  is

$$S_0 = s$$

$$S_1 = \begin{cases} s \cdot u, & \text{with probability } p_u \\ s \cdot d, & \text{with probability } p_d \end{cases}$$

- ▶ The process can also be written as

$$S_0 = s$$

$$S_1 = s \cdot Z$$

- ▶ The random variable  $Z$  is then defined by

$$Z = \begin{cases} u, & \text{with probability } p_u \\ d, & \text{with probability } p_d \end{cases}$$

# Basic assumptions

- ▶ The following quantities are known at time  $t = 0$ 
  - ▶ the interest rate,  $R$
  - ▶ the current stock price,  $s$
  - ▶ the stock move coefficients,  $u$  and  $d$
  - ▶ the probabilities,  $p_u$  and  $p_d$
- ▶ We assume stock move coefficients are such that  $d < u$
- ▶ Naturally, probabilities are *exhaustive*, hence  $p_u + p_d = 1$



# Portfolio

- ▶ We want to form portfolios of the two assets featured in the model
- ▶ A **portfolio** is defined as the vector  $h = (x, y)$ , where
  - ▶  $x$  is the number of bonds we hold in our portfolio
  - ▶  $y$  is the number of units of the stock
- ▶  $x$  and  $y$  may be positive as well as negative, for example
  - ▶  $x = 3$  means that we hold three bonds at  $t = 0$
  - ▶  $y = -2$  means that we owe two shares of the stock at  $t = 0$
  - ▶ we have a *long* position in the bond and a *short* position in the stock

# Assumptions on portfolio formation

- ▶ *Short positions*, as well as *fractional holdings*, are allowed

$\forall h \in R^2$  is a feasible portfolio

- ▶ There is *no bid-ask spread*: selling price equals buying price
- ▶ There are *no transactions costs*
- ▶ The market is *completely liquid*
  - ▶ it is always possible to buy/sell unlimitedly at the market price
  - ▶ it is possible to borrow unlimitedly from the bank (sell bonds short)

# Value process of a portfolio

- ▶ The portfolio value is simply the sum of the values of the assets held
  - ▶ it has a deterministic market value at  $t = 0$
  - ▶ it has a stochastic value at  $t = 1$  (unless  $y = 0$ )
- ▶ Formally, the value process for  $h$  is

$$V_t^h = xB_t + yS_t, \quad t = 0, 1$$

- ▶ More explicitly

$$V_0^h = x + ys$$

$$V_1^h = x(1 + R) + ysZ$$

# Arbitrage portfolio

- ▶ Can one make positive profit for sure by trading on the market?
- ▶ We call a portfolio that guarantees just that an **arbitrage portfolio**
  - ▶ Formally,  $h$  is an arbitrage portfolio if:

$$V_0^h = 0$$

$$V_1^h > 0, \text{ with probability } 1$$

- ▶ An arbitrage portfolio is thus a deterministic money making machine
- ▶ We interpret the existence of an arbitrage portfolio as equivalent to a serious case of mispricing on the market

# No-arbitrage condition

- ▶ When is a given market model arbitrage free?
- ▶ That is to say, when are there *no arbitrage portfolios*?
- ▶ The binomial model is **free of arbitrage** if and only if

$$d \leq 1 + R \leq u \quad (1)$$

- ▶ This inequality implies that
  - ▶ the bond payoff is not allowed to *dominate* the stock payoff
  - ▶ and vice versa!

# Violation of the condition

- ▶ To see that our claim is correct
  - ▶ we first show that the no arbitrage condition implies inequality (1)
  - ▶ if the inequality *does not* hold, then we have an arbitrage opportunity
- ▶ Suppose that

$$(1 + R) > u$$

- ▶ this inequality implies  $s(1 + R) > su$
  - ▶ since  $u > d$ , we also have  $su > sd$
- ▶ As a result, it is always more profitable to invest in the bond

$$s(1 + R) > su > sd$$

- ▶ An arbitrage strategy is then formed by the portfolio  $h = (s, -1)$ 
  - ▶ we sell the stock short
  - ▶ we invest all the money in the bond

# Violation of the condition

- ▶ At  $t = 0$ , the value of this portfolio is obviously zero

$$V_0^h = x + ys = s + (-1)s = 0$$

- ▶ At  $t = 1$  the value of this portfolio is always positive

$$V_1^h = x(1 + R) + ysZ = \begin{cases} s(1 + R) - su > 0 \\ s(1 + R) - sd > 0 \end{cases}$$

- ▶ To avoid this arbitrage opportunity, it must then be that

$$1 + R \leq u$$

**Exercise** Repeat the argument after assuming that  $(1 + R) < d$

# Arbitrage-free market

- ▶ We now turn to show that inequality (1) implies no arbitrage
- ▶ If the inequality *does* hold, then we have no arbitrage opportunity
- ▶ Consider an arbitrary portfolio such that  $V_0^h = 0$
- ▶ We have  $x + ys = 0$ , which in turn yields

$$x = -ys$$

- ▶ The value of the portfolio at  $t = 1$  is then

$$V_1^h = \begin{cases} -ys(1+R) + ysu = ys[u - (1+R)], & \text{if } Z = u \\ -ys(1+R) + ysd = ys[d - (1+R)], & \text{if } Z = d \end{cases}$$

# Arbitrage-free market

- ▶ Suppose that  $y > 0$ 
  - ▶ Then  $h$  is an arbitrage strategy if and only if we have

$$s[u - (1 + R)] > 0$$

$$s[d - (1 + R)] > 0$$

- ▶ This implies

$$u > 1 + R$$

$$d > 1 + R$$

- ▶ But this violates inequality (1), since it requires  $d \leq 1 + R$

**Exercise** Repeat the argument after assuming that  $y < 0$

# Interpretation of the no-arbitrage condition

- ▶ How can we interpret this result?
- ▶ If inequality (1) holds, then a pair  $(q_u, q_d)$  exists, with  $q_u \geq 0$ ,  $q_d \geq 0$ , and  $q_u + q_d = 1$ , such that

$$1 + R = q_u \cdot u + q_d \cdot d$$

**Interpretation**  $(q_u, q_d)$  represent a new probability measure  $Q$ , with

$$Q(Z = u) = q_u$$

$$Q(Z = d) = q_d$$

# Risk-neutral valuation formula

- ▶ We may compute the discounted (at rate  $R$ ) expected value of  $S_1$  using the probability measure  $Q$  (denoted by  $E^Q$ )

$$\frac{1}{1+R} E^Q [S_1] = \frac{1}{1+R} (q_u s u + q_d s d) = \frac{s}{1+R} \overbrace{(q_u u + q_d d)}^{1+R} = s$$

- ▶ We thus obtain the **risk-neutral valuation formula**

$$s = \frac{1}{1+R} E^Q [S_1]$$

- ▶ it gives today's stock price as the discounted expected value of tomorrow's stock price
- ▶ we do *not* assume that agents are risk neutral
- ▶ merely, if we use the  $Q$ -probabilities instead of the objective ones, then we get a risk neutral valuation of the stock

# Risk-neutral probability

- ▶ The probability measure  $Q$  is called a risk-neutral measure, or alternatively a risk-adjusted measure or a martingale measure
- ▶ Formally,  $Q$  is a martingale measure if

$$S_0 = \frac{1}{1+R} E^Q [S_1]$$

- ▶ We can also re-state the no arbitrage condition: the binomial model is arbitrage free if and only if there exists a martingale measure  $Q$
- ▶ For the binomial model, the martingale probabilities are

$$\begin{cases} q_u = \frac{(1+R) - d}{u - d} \\ q_d = \frac{u - (1+R)}{u - d} \end{cases}$$

# Risk-neutral probability

- ▶ Obtaining them is easy; we begin by the definition equations

$$\begin{cases} 1 + R = q_u u + q_d d \\ q_u + q_d = 1 \end{cases}$$

- ▶ Obtain from the second  $q_d = 1 - q_u$ ; then substitute into the first

$$\begin{aligned} 1 + R &= q_u u + (1 - q_u) d \\ &= q_u (u - d) + d \end{aligned}$$

- ▶ Isolating  $q_u$ , we obtain the first probability
- ▶ Replacing it into  $q_d = 1 - q_u$ , we obtain the second

# Definition of financial derivative

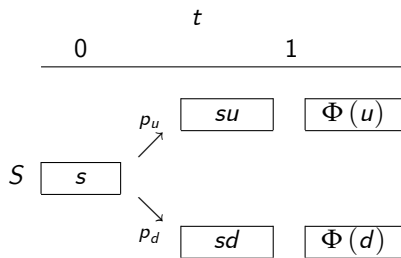
- ▶ We define a financial derivative (contingent claim) as a stochastic variable  $X$  of the form

$$X = \Phi(Z)$$

where, as before,

$$Z = \begin{cases} u, & \text{with probability } p_u \\ d, & \text{with probability } p_d \end{cases}$$

# Tree diagram



# Example of financial derivative

- ▶ Consider a European call option on  $S$  with exercise price  $K$
- ▶ The example is interesting only if  $sd < K < su$ 
  - ▶ when  $S_1 = su > K$ 
    - ▶ we use the option, paying  $K$  to get the stock
    - ▶ we sell the stock on the market for  $su$
    - ▶ we make a net profit of  $su - K$
  - ▶ when  $S_1 = sd < K$ , then the option is obviously worthless
- ▶ We therefore have the payoff structure

$$X = \begin{cases} \Phi(u) = su - K, & \text{if } Z = u \\ \Phi(d) = 0, & \text{if } Z = d \end{cases}$$

# Price of a financial derivative

- ▶ We now turn to determine the “fair” price of a financial derivative
- ▶ We denote the price of  $X$  at time  $t$  by  $\Pi(t; X)$
- ▶ At  $t = 1$ , in order to avoid arbitrage, we must have

$$\Pi(1; X) = X$$

- ▶ If  $\Pi(1; X) < X$ , then one can obtain an instant profit by buying the derivative for  $\Pi(1; X)$  and cash in its payoff  $X$
- ▶ If  $\Pi(1; X) > X$ , one would sell short the derivative for  $\Pi(1; X)$  and pay it back using part of its payoff  $X$

# Price of a financial derivative

- ▶ We now tackle the harder issue of determining  $\Pi(0; X)$
- ▶ We first define a hedging portfolio
- ▶ We then characterize a complete market
- ▶ We show that an arbitrage-free binomial model is complete
- ▶ We finally work out the price process for the derivative

# Hedging portfolio

- ▶ A given derivative  $X$  is **reachable** if there exists a portfolio  $h$  such that, with probability one

$$V_1^h = X$$

- ▶ In this case,  $h$  is a **hedging portfolio** or a **replicating portfolio**
- ▶ If a certain derivative  $X$  is reachable with replicating portfolio  $h$ , then
  - ▶ there is no difference between holding the derivative and holding the portfolio
  - ▶ no matter what happens on the stock market, the derivative value at  $t = 1$  will be exactly equal to the portfolio value at  $t = 1$
- ▶ *The derivative price equals the market value of the portfolio*

# Hedging portfolio and no-arbitrage condition

- ▶ Formally, if  $X$  is reachable with a replicating portfolio  $h$ , then the only *reasonable* price process for  $X$  is

$$\Pi(t; X) = V_t^h, \quad t = 0, 1$$

- ▶ Any  $\Pi(0; X)$  other than  $V_0^h$  will lead to an arbitrage opportunity

# Hedging portfolio and no-arbitrage condition

- ▶ Suppose that  $V_0^h < \Pi(0; X)$
- ▶ At  $t = 0$ 
  - ▶ We short sell  $X$
  - ▶ We buy  $h$
  - ▶ We use the difference to purchase bonds
- ▶ At  $t = 1$ 
  - ▶ the payoff of  $X$  and  $h$  coincide by definition
  - ▶ hence the net worth of this portion of the portfolio is zero
  - ▶ the bonds yield  $(\Pi(0; X) - V_0^h)(1 + R) > 0$ , an arbitrage profit

**Exercise** Repeat the argument after assuming that  $V_0^h > \Pi(0; X)$

# Complete market

- ▶ A **market** is **complete** if all derivatives can be replicated
- ▶ This implies that in a complete market we can price all derivatives
- ▶ Thus, it is crucial to investigate when a given market is complete
- ▶ For the binomial model, we have that the market is complete if the model is arbitrage-free

# Hedging portfolio for a generic derivative

- ▶ Consider an arbitrary derivative  $X = \Phi(Z)$
- ▶ We want to show that there exists a portfolio  $h = (x, y)$  such that

$$V_1^h = \Phi(u), \text{ if } Z = u$$

$$V_1^h = \Phi(d), \text{ if } Z = d$$

- ▶ Specifically, we seek a solution  $(x, y)$  to the system of equations

$$(1 + R)x + suy = \Phi(u)$$

$$(1 + R)x + sdy = \Phi(d)$$

# Hedging portfolio for a generic derivative

- ▶ We isolate  $x$  in the first equation

$$x = \frac{\Phi(u) - suy}{1 + R}$$

- ▶ We replace it into the second, obtaining

$$x = \frac{1}{1 + R} \frac{u\Phi(d) - d\Phi(u)}{u - d}$$

$$y = \frac{1}{s} \frac{\Phi(u) - \Phi(d)}{u - d}$$

- ▶ these two expressions give us the number of bonds and stock shares, respectively, that we need to hold in the portfolio to replicate  $X$

# Risk Neutral Valuation

- ▶ Since the hedging portfolio exists for any arbitrary derivative  $X$ , then the binomial model is shown to be complete
- ▶ We can thus price the derivative using the expression

$$\Pi(0; X) = V_0^h$$

- ▶ Recall that the value of a portfolio  $h$  at  $t = 0$  is

$$V_0^h = x + ys$$

- ▶ Recall also that the martingales probabilities are

$$\begin{cases} q_u = \frac{(1+R) - d}{u - d} \\ q_d = \frac{u - (1+R)}{u - d} \end{cases}$$

# Risk Neutral Valuation

- ▶ Then, using the hedging portfolio holdings, we have

$$\begin{aligned}\Pi(0; X) &= x + sy \\ &= \frac{1}{1+R} \frac{u\Phi(d) - d\Phi(u)}{u-d} + \frac{1}{s} \frac{\Phi(u) - \Phi(d)}{u-d} \cdot s \\ &= \frac{1}{1+R} \left[ \frac{u\Phi(d) - d\Phi(u)}{u-d} + (1+R) \frac{\Phi(u) - \Phi(d)}{u-d} \right] \\ &= \frac{1}{1+R} \left[ \underbrace{\frac{(1+R) - d}{u-d}}_{q_u} \Phi(u) + \underbrace{\frac{u - (1+R)}{u-d}}_{q_d} \Phi(d) \right]\end{aligned}$$

# Risk Neutral Valuation

- ▶ Since the binomial model is arbitrage-free, then  $d \leq (1 + R) \leq u$
- ▶ Hence  $(q_u, q_d)$  are *probabilities* (non negative, sum up to one) and

$$\Pi(0; X) = \frac{1}{1 + R} [\Phi(u) \cdot q_u + \Phi(d) \cdot q_d] = \frac{1}{1 + R} E^Q(\Phi(Z))$$

- ▶ the right-hand side can now be interpreted as an expected value under the martingale probability measure  $Q$
- ▶ the price process of a derivative is just the *discounted expected value of its payoff, computed using risk neutral probabilities*

# Binomial model recap

- ▶ If the binomial model is free of arbitrage, then the arbitrage-free price of a derivative  $X$  is given by

$$\Pi(0; X) = \frac{1}{1+R} E^Q [X]$$

- ▶ The martingale measure  $Q$  is uniquely determined by the relation

$$S_0 = \frac{1}{1+R} E^Q [S_1]$$

- ▶ The explicit expression for the probabilities are given by

$$\begin{cases} q_u = \frac{(1+R) - d}{u - d} \\ q_d = \frac{u - (1+R)}{u - d} \end{cases}$$

# Binomial model recap

- ▶ The derivative can be replicated by a portfolio  $h = (x, y)$  such that

$$x = \frac{1}{1+R} \frac{u\Phi(d) - d\Phi(u)}{u-d}$$
$$y = \frac{1}{s} \frac{\Phi(u) - \Phi(d)}{u-d}$$

- ▶ The objective probabilities determine which events are possible
- ▶ The risk neutral probabilities simplify the computations of the arbitrage-free price of a financial derivative
- ▶ This does not mean that we live in a risk-neutral world
- ▶ The formula holds for all investors, regardless of their attitude towards risk, as long as they prefer more deterministic money to less

# An illustrative example

► We set

- $s = 100$
- $u = 1.2$  and  $d = 0.8$
- $p_u = 0.6$ , hence  $p_d = 0.4$
- $R = 0$

► Thus we have the price dynamics

$$\begin{aligned} S_0 &= 100 \\ S_1 &= \begin{cases} 120, & \text{with probability } 0.6 \\ 80, & \text{with probability } 0.4 \end{cases} \end{aligned}$$

►  $d \leq (1 + R) \leq u$  holds, hence the market is arbitrage-free

$$d = 0.8 < 1 = 1 + R < 1.2 = u$$

# An illustrative example

- ▶ We consider a **European call option** with strike price  $K = 110$

[en.wikipedia.org/wiki/Call\\_option](https://en.wikipedia.org/wiki/Call_option)

- ▶ So (the payoff of) the derivative  $X$  is given by:

$$X = \max(S_1 - K, 0) = \begin{cases} 10, & \text{with probability } 0.6 \\ 0, & \text{with probability } 0.4 \end{cases}$$

- ▶ Using the (*naive*) method of computing the price as the discounted expected values under the objective probabilities, we would get

$$\Pi^P(0; X) = \frac{1}{1+0} [10 \cdot 0.6 + 0 \cdot 0.4] = 6$$

# Price of the European call option

- ▶ Using the theory above it is easily seen that the martingale probabilities are given by

$$\begin{cases} q_u = \frac{(1+R) - d}{u - d} = \frac{(1+0) - 0.8}{1.2 - 0.8} = 0.5 \\ q_d = \frac{u - (1+R)}{u - d} = \frac{1.2 - (1+0)}{1.2 - 0.8} = 0.5 \end{cases}$$

- ▶ Thus the theoretical price is

$$\Pi(0; X) = \frac{1}{1+0} [10 \cdot 0.5 + 0 \cdot 0.5] = 5$$

- ▶ The theoretical price differs (is lower than) its *naive* counterpart

# Hedging portfolio of the European call option

- ▶ To verify our finding, we replicate the option
- ▶ Using the hedging portfolio holding stated above, we obtain

$$x = \frac{1}{1+R} \frac{u\Phi(d) - d\Phi(u)}{u-d} = \frac{1}{1+0} \frac{1.2 \cdot 0 - 0.8 \cdot 10}{1.2 - 0.8} = -20$$

$$y = \frac{1}{s} \frac{\Phi(u) - \Phi(d)}{u-d} = \frac{1}{100} \frac{10 - 0}{1.2 - 0.8} = \frac{1}{4}$$

- ▶ The replicating portfolio is then formed by
  - ▶ borrowing 20 from the bank
  - ▶ investing this money to (partially) fund the purchase of a quarter of a share in the stock

# Replication of the European call option

- ▶ Thus the net value of the portfolio at  $t = 0$  is

$$V_0^h = x + ys = -20 + \frac{1}{4} \cdot 100 = 5$$

- ▶ At  $t = 1$  it replicates the option payoff, as it is given by

$$V_1^h = x(1 + R) + yS_1 = -20(1 + 0) + \frac{1}{4} \cdot 120 = 10, \quad \text{if } S_1 = 120$$

$$V_1^h = x(1 + R) + yS_1 = -20(1 + 0) + \frac{1}{4} \cdot 80 = 0, \quad \text{if } S_1 = 80$$

# Illustrative example wrap-up

- ▶ So we see that we have indeed replicated the option
- ▶ We also see that if anyone is foolish enough to buy the option from us for 6, then we can make a riskless profit
- ▶ We sell the option, thereby obtaining 6
- ▶ Out of these 6 we invest five in the replicating portfolio and invest the remaining one in the bank
- ▶ At  $t = 1$ , the claims of the buyer of the option are completely balanced by the value of the replicating portfolio, and we still have one dollar (plus interest) invested in the bank
- ▶ We have thus made an arbitrage profit
- ▶ If someone is willing to sell the option to us at a price lower than five dollars, we can also make an arbitrage profit by selling the portfolio short

# Theoretical take-away

- ▶ We have seen that in a complete market, like the binomial model above, there is indeed a unique price for any derivative
- ▶ The price is given by the value of the replicating portfolio
- ▶ In fact, there exists a theoretical price for the derivative precisely because, strictly speaking, the derivative is superfluous
- ▶ *The derivative can equally well be replaced by its hedging portfolio*

# Theoretical take-away

- ▶ We see that the structural reason for the completeness of the binomial model is that
  - ▶ we have two financial instruments at our disposal (bond and stock)
  - ▶ to solve two equations (one for each possible outcome)
- ▶ This fact can be generalized
- ▶ *A model is complete if the number of underlying assets (including the bank account) equals the number of outcomes*

# Theoretical take-away

- ▶ If we would like to make a more realistic multiperiod model of the stock market, then the last remark above seems discouraging
- ▶ If we make a (non-recombining) tree with 20 time steps this means that we have  $2^{20} \sim 10^6$  elementary outcomes
- ▶ This number exceeds by a large margin the number of assets on any existing stock market
- ▶ It would *seem* that it is impossible to construct an interesting complete model with a reasonably large number of time steps

# Theoretical take-away

- ▶ Fortunately the situation is not at all as bad as that
- ▶ In a multiperiod model we also have the possibility of considering intermediary trading
- ▶ We can thus allow for portfolios which are rebalanced over time
- ▶ This will give us many more degrees of freedom

# Theoretical take-away

- ▶ Finally, note that the source of risk is clearly identified, and (ex-post) observed, in the underlying risky asset of the derivative
- ▶ Unfortunately, this is not the case for the entire market
- ▶ This is the reason why this line of reasoning does not apply to a macroeconomic asset pricing approach

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1. Basic risk management strategies
2. Binomial model
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5. Classical hedging strategies
6. Continuous-time options

# Market structure

- ▶ The time index is  $t = 0, \dots, T$ , where the horizon  $T$  is fixed
- ▶ As before, we have two assets
  - ▶ a risk free asset (bond), with price  $B_t$  at time  $t$
  - ▶ a risky asset (stock), with price  $S_t$  at time  $t$
- ▶ The price process  $B$  is redefined as

$$\begin{array}{l} B_0 = 1 \\ B_1 = 1 + R \end{array} \quad \rightarrow \quad \begin{array}{l} B_0 = 1 \\ B_{t+1} = (1 + R) B_t \end{array}$$

- ▶  $R$  is the (*known*) *constant* deterministic return rate for each period
  - ▶ the bond is still interpreted as a bank deposit with interest rate  $R$
  - ▶ the first period process is unchanged, since setting  $t = 0$  yields

$$B_1 = (1 + R) B_0 = 1 + R$$

# Market structure

- ▶ The price process  $S$  is redefined as

$$\begin{array}{l} S_0 = s \\ S_1 = s \cdot Z \end{array} \quad \rightarrow \quad \begin{array}{l} S_0 = s \\ S_{t+1} = S_t \cdot Z_t \end{array}$$

- ▶ Each  $Z_t$  is still the random variable

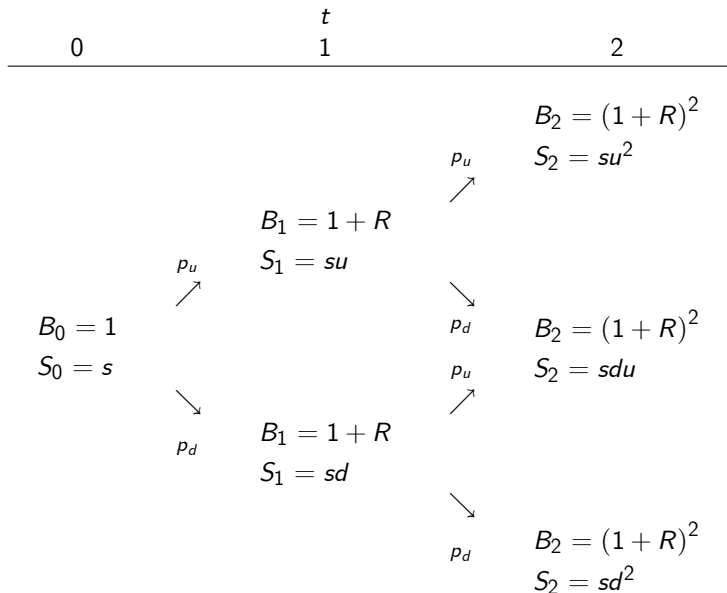
$$Z_t = \begin{cases} u, & \text{with probability } p_u \\ d, & \text{with probability } p_d \end{cases}$$

- ▶  $Z_0, \dots, Z_{T-1}$  are i.i.d. (independent and identically distributed)
- ▶ the first period process is unchanged, since setting  $t = 0$  yields

$$S_1 = S_0 \cdot Z_0 = s \cdot Z$$

- ▶ we purposely drop the time subscript (possible given the i.i.d. assumption) to stress the parallel to the one-period model

# Tree diagram



# Portfolio

- ▶ We want to form portfolios of the two assets featured in the model
- ▶ We redefine a portfolio as the stochastic process

$$h = (x, y) \rightarrow h_t = (x_t, y_t), t = 1, \dots, T$$

- ▶ The portfolio's value process becomes

$$V_t^h = xB_t + yS_t, t = 0, 1 \rightarrow V_t^h = x_t(1 + R) + y_tS_t, t = 1, \dots, T$$

- ▶ Understanding the model's timing is crucially important here
  - ▶  $x_t$  is the amount we invest in bonds at  $t - 1$  and keep until  $t$
  - ▶  $y_t$  is the number of shares that we buy at  $t - 1$  and keep until  $t$
  - ▶  $V_t^h$  is therefore the market value of the portfolio  $(x_t, y_t)$  at time  $t$  (which we held since  $t - 1$ )

# Assumptions on portfolio formation

- ▶ *Short positions*, as well as *fractional holdings*, are allowed

$\forall h \in R^2$  is a feasible portfolio

- ▶ There is *no bid-ask spread*: selling price equals buying price
- ▶ There are *no transactions costs*
- ▶ The market is *completely liquid*
  - ▶ it is always possible to buy/sell unlimitedly at the market price
  - ▶ it is possible to borrow unlimitedly from the bank (sell bonds short)

# Self-financing portfolio

- ▶ We are primarily interested in **self-financing portfolios**

[en.wikipedia.org/wiki/Self-financing\\_portfolio](https://en.wikipedia.org/wiki/Self-financing_portfolio)

- ▶ modified over time without exogenous money infusion nor withdrawal
- ▶ the accession of new assets must be financed through selling others
- ▶ Formally, a portfolio  $h$  is self financing if  $V_t^h = V_{t+1}^h$  for all  $t = 0, \dots, T - 1$ 
  - ▶ in turn, this implies

$$x_t(1 + R) + y_t S_t = x_{t+1} + y_{t+1} S_t$$

- ▶ the expression simply represents a budget equation, so that
- ▶ at each  $t$ , the market value of  $(x_t, y_t)$ , created at  $t - 1$ , equals the purchase value of  $(x_{t+1}, y_{t+1})$ , formed at  $t$  (and held until  $t + 1$ )

# Arbitrage portfolio

- ▶ Redefine the arbitrage portfolio a *self-financing* portfolio  $h$  such that

$$\begin{array}{l} V_0^h = 0 \\ V_1^h > 0, \text{ with probability } 1 \end{array} \quad \rightarrow \quad \begin{array}{l} V_0^h = 0 \\ P(V_T^h \geq 0) = 1 \\ P(V_T^h > 0) > 0 \end{array}$$

- ▶ The arbitrage portfolio need *not* be strictly positive *in every state*
- ▶ An arbitrage portfolio can nonetheless still be interpreted as a money making machine, just not *deterministic*

# Arbitrage-free market

- ▶ The binomial model is free of arbitrage if and only if

$$d \leq 1 + R \leq u$$

- ▶ The risk-neutral valuation formula is redefined as

$$s = \frac{1}{1+R} E^Q [S_1] \quad \rightarrow \quad s = \frac{1}{1+R} E^Q [S_{t+1} | S_t = s]$$

- ▶ the expectation is now conditioned on the current stock value  $S_t$
  - ▶  $S_t$  is of course time-dependent (on the realizations of  $S$  up to time  $t$ )
- ▶ The martingale probabilities are still given by

$$\begin{cases} q_u = \frac{(1+R) - d}{u - d} \\ q_d = \frac{u - (1+R)}{u - d} \end{cases}$$

# Definition of financial derivative

- ▶ We redefine a financial derivative as

$$X = \Phi(Z) \rightarrow X = \Phi(S_T)$$

- ▶ the reason is that now an entire set of random variables  $\{Z\}$  jointly determine the value of the stock at maturity
- ▶ hence, it is more convenient to refer to  $S_T$  rather than writing  $X = \Phi(Z_0, Z_1, \dots, Z_{T-1})$ , equally correct but more cumbersome
- ▶ We still denote the price of  $X$  at time  $t$  by  $\Pi(t; X)$ 
  - ▶ formally, we have

$$\Pi(t; X), \text{ for } t = 0, \dots, T$$

- ▶ the only difference is that now  $t$  indexes more than two dates

# Hedging portfolio

- ▶ As before, a given derivative  $X$  is **reachable** if there exists a portfolio  $h$  such that, with probability one

$$V_T^h = X$$

- ▶ The difference is that  $h$  is now a **self-financing** hedging portfolio
- ▶ Once again, from a financial point of view there is no difference between holding the derivative or the portfolio
  - ▶ suppose that  $X$  is reachable using the self-financing portfolio  $h$
  - ▶ fix  $t$  and suppose that at time  $t$  we have access to the amount  $V_t^h$
  - ▶ then we can invest this money in the portfolio  $h$
  - ▶ rebalance  $h$  over time without extra cost so as to have  $V_T^h$  at time  $T$
  - ▶ by definition  $V_T^h = X$  with probability 1
  - ▶ thus, from a financial point of view,  $h$  and  $X$  are equivalent so they should fetch the same price

# Price of a financial derivative

- ▶ Formally, if  $X$  is reachable with a replicating portfolio  $h$ , then the only *reasonable* price process for  $X$  is

$$\Pi(t; X) = V_t^h, \quad t = 0, 1, \dots, T$$

- ▶ Any price other than  $V_\tau^h$  at time  $\tau$  leads to an arbitrage opportunity
  - ▶ suppose that  $V_\tau^h < \Pi(\tau; X)$
  - ▶ at  $\tau$ , we short sell  $X$ , buy  $h$  and purchase bonds with the difference
  - ▶ at  $T$  the payoffs of  $X$  and  $h$  coincide by definition
  - ▶ selling the bonds yields  $(\Pi(\tau; X) - V_\tau^h)(1 + R)^{T-\tau} > 0$
  - ▶ we have an arbitrage profit

**Exercise** Repeat the argument after assuming that  $V_\tau^h > \Pi(\tau; X)$

# Complete market

- ▶ **As before**, we define the **market** as **complete** if all derivatives can be replicated
- ▶ This implies that in a complete market we can price all derivatives
- ▶ Therefore, it is crucial to investigate when a given market is complete
- ▶ It is possible, and not very hard, to give a formal proof which, however, look rather messy with lots of indices
- ▶ We therefore prove completeness for a concrete example instead

# Example setup

- Let  $T = 3$ ,  $S_0 = 80$ ,  $u = 1.5$ ,  $d = 0.5$ ,  $p_u = 0.6$ ,  $p_d = 0.4$ ,  $R = 0$

			$B_3 = 1$ $S_3 = 270$
		$B_2 = 1$ $S_2 = 180$	
	$B_1 = 1$ $S_1 = 120$		$B_3 = 1$ $S_3 = 90$
$B_0 = 1$ $S_0 = 80$		$B_2 = 1$ $S_2 = 60$	
	$B_1 = 1$ $S_1 = 40$		$B_3 = 1$ $S_3 = 30$
		$B_2 = 1$ $S_2 = 20$	
			$B_3 = 1$ $S_3 = 10$

# Financial derivative

- ▶ Consider a European call option on the underlying stock
  - ▶ the date of expiration of the option is  $T = 3$
  - ▶ the strike price is chosen to be  $K = 80$
  - ▶ Formally this claim can be described as

$$X = \max[S_T - K, 0]$$

- ▶ We will now show that this particular claim can be replicated
  - ▶ it will be obvious from the argument that the result can be generalized to any binomial model and any claim
  - ▶ the idea is to use induction on the time variable and to work backwards in the tree from the leaves at  $t = T$  to the root at  $t = 0$
- ▶ We start by computing the price of the option at the expiration date
  - ▶ this is easily done since obviously we must have, for any claim  $X$

$$\Pi(T; X) = X$$

# Tree diagram for the underlying and derivative

			$S_3 = 270$ $\Pi_3 = 190$
		$S_2 = 180$ $\Pi_2 = ?$	
	$S_1 = 120$ $\Pi_1 = ?$		$S_3 = 90$ $\Pi_3 = 10$
$S_0 = 80$ $\Pi_0 = ?$		$S_2 = 60$ $\Pi_2 = ?$	
	$S_1 = 40$ $\Pi_1 = ?$		$S_3 = 30$ $\Pi_3 = 0$
		$S_2 = 20$ $\Pi_2 = ?$	
			$S_3 = 10$ $\Pi_3 = 0$

# Partitioning the tree diagram

- ▶ Our problem is now to replicate the payoff structure at  $t = 3$ 
  - ▶ consider some node at  $t = 2$ , for instance the node  $S_2 = 180$
  - ▶ we face the diagram of a simple one-period binomial model

$$S_2 = 180$$
$$\Pi_2 = ?$$

$$S_3 = 270$$
$$\Pi_3 = 190$$

$$S_3 = 90$$
$$\Pi_3 = 10$$

# Pricing the derivative within the sub-diagram

- ▶ It follows from the one-period theory that the payoff structure can indeed be replicated from the node  $S_2 = 180$
- ▶ If that is the case, then we can compute the price of the replicated claim by risk-neutral valuation
  - ▶ we need to calculate the martingale probabilities

$$\begin{cases} q_u = \frac{(1+R) - d}{u - d} = \frac{(1+0) - 0.5}{1.5 - 0.5} = 0.5 \\ q_d = \frac{u - (1+R)}{u - d} = \frac{1.5 - (1+0)}{1.5 - 0.5} = 0.5 \end{cases}$$

- ▶ and apply the risk-neutral valuation formula

$$\Pi(2; X) = \frac{1}{1+R} E^Q [X] = \frac{1}{1+0} [190 \cdot 0.5 + 10 \cdot 0.5] = 100$$

# Pricing the derivative within the other sub-diagrams

			$S_3 = 270$ $\Pi_3 = 190$
		$S_2 = 180$ $\Pi_2 = 100$	
	$S_1 = 120$ $\Pi_1 = ?$		$S_3 = 90$ $\Pi_3 = 10$
$S_0 = 80$ $\Pi_0 = ?$		$S_2 = 60$ $\Pi_2 = 5$	
	$S_1 = 40$ $\Pi_1 = ?$		$S_3 = 30$ $\Pi_3 = 0$
		$S_2 = 20$ $\Pi_2 = 0$	
			$S_3 = 10$ $\Pi_3 = 0$

# Pricing the derivative in the rest of the diagram

- ▶ If a self-financing portfolio replicates the claim at  $t = 2$ 
  - ▶ then it is possible to price at  $t = 2$  the claim's payoff at  $t = 3$
  - ▶ we have thus reduced the problem in the time variable
- ▶ We thus simply need to reproduce the same procedure at  $t = 1$ 
  - ▶ take, for example, the node  $S_1 = 40$
  - ▶ from the point of view of this node, we have

$$\begin{array}{r} S_2 = 60 \\ \Pi_2 = 5 \\ \\ S_1 = 40 \\ \Pi_1 = ? \\ \\ S_2 = 20 \\ \Pi_2 = 0 \end{array}$$

- ▶ By risk neutral valuation we can price this payoff structure

$$\Pi(1; X) = \frac{1}{1+R} E^Q [X] = \frac{1}{1+0} [5 \cdot 0.5 + 0 \cdot 0.5] = 2.5$$

# Pricing the derivative in the rest of the diagram

- In this manner we fill the nodes at  $t = 1$  with the claim prices, then apply the procedure again at  $t = 0$

			$S_3 = 270$ $\Pi_3 = 190$
		$S_2 = 180$ $\Pi_2 = 100$	
	$S_1 = 120$ $\Pi_1 = 52.5$		$S_3 = 90$ $\Pi_3 = 10$
$S_0 = 80$ $\Pi_0 = 27.5$		$S_2 = 60$ $\Pi_2 = 5$	
	$S_1 = 40$ $\Pi_1 = 2.5$		$S_3 = 30$ $\Pi_3 = 0$
		$S_2 = 20$ $\Pi_2 = 0$	
			$S_3 = 10$ $\Pi_3 = 0$

# Hedging portfolio at $t = 0$

- ▶ For now, we have just shown how to price *backward* an European call option *if* a self-financing portfolio replicates the claim
- ▶ To prove market completeness, we need to show that a self-financing portfolio *does reach* the option
- ▶ We do so by following a possible price path *forward* through the tree
- ▶ We start at  $t = 0$  and reproduce the claim  $(52.5, 2.5)$  at  $t = 1$

$$V_1^h = \begin{cases} x_1(1+0) + y_1 \cdot 80 \cdot 1.5 = 52.5 \\ x_1(1+0) + y_1 \cdot 80 \cdot 0.5 = 2.5 \end{cases}$$

- ▶ we isolate  $x_1$

$$\begin{cases} x_1 = 52.5 - 120y_1 \\ x_1 = 2.5 - 40y_1 \end{cases}$$

- ▶ we merge the two equations and solve for  $y_1$  then for  $x_1$

$$\begin{aligned} (120 - 40)y_1 &= 52.5 - 2.5 \rightarrow y_1 = 0.625 \\ x_1 &= 2.5 - 40 \cdot 0.625 = -22.5 \end{aligned}$$

# Hedging portfolio at $t = 0$

- ▶ The hedging portfolio's value at  $t = 0$  is the same as the claim's

$$V_0^h = -22.5 + 80 \frac{5}{8} = 27.5 = \Pi_0$$

- ▶ If the price now moves to  $S_1 = 120$ , the portfolio is worth

$$V_1^h = -22.5 \cdot (1 + 0) + \frac{5}{8} \cdot 120 = 52.5$$

- ▶ Otherwise, with  $S_1 = 40$ , we have

$$V_1^h = -22.5 \cdot (1 + 0) + \frac{5}{8} \cdot 40 = 2.5$$

- ▶ Portfolio  $h$  has the same payoff structure (and value!) as  $X$

# Hedging portfolio at $t = 1$

- ▶ Suppose to face the claim  $(100, 5)$  at  $t = 2$ , so we impose

$$V_2^h = \begin{cases} x_2(1+0) + y_2 \cdot 120 \cdot 1.5 = 100 \\ x_2(1+0) + y_2 \cdot 120 \cdot 0.5 = 5 \end{cases}$$

- ▶ We isolate  $x_2$ , merge the two equations and solve for  $y_2$  then for  $x_2$

$$\begin{aligned} 100 - 180y_2 &= 5 - 60y_2 \rightarrow y_2 = 95/120 \approx 0.792 \\ x_2 &= 5 - 60 \cdot 95/120 = -42.5 \end{aligned}$$

- ▶ The cost of this portfolio equals the value of our old portfolio

$$V_1^h = -42.5 + 120 \frac{95}{120} = 52.5$$

- ▶ Thus, the replicating portfolio is also self-financing

## Hedging portfolio at $t = 2$

- ▶ If the price falls to  $S_2 = 60$ , then our portfolio is worth

$$V_2^h = -42.5 \cdot (1 + 0) + \frac{95}{120} \cdot 60 = 5$$

- ▶ Facing the claim  $(10, 0)$  at  $t = 3$ , we impose

$$V_3^h = \begin{cases} x_3 (1 + 0) + y_3 \cdot 60 \cdot 1.5 = 10 \\ x_3 (1 + 0) + y_3 \cdot 60 \cdot 0.5 = 0 \end{cases}$$

- ▶ We isolate  $x_3$ , merge the two equations and solve for  $y_3$  then for  $x_3$

$$\begin{aligned} 10 - 90y_3 &= -30y_3 \rightarrow y_3 = 1/6 \approx 0.167 \\ x_3 &= -30/6 = -5 \end{aligned}$$

- ▶ Once again, the cost equals the old portfolio's value

$$V_2^h = -5 + 60 (1/6) = 5$$

## Hedging portfolio at $t = 3$

- ▶ If the price rises to  $S_3 = 90$ , then our portfolio is exactly valued as the option payoff at that node in the tree

$$V_3^h = -5 \cdot (1 + 0) + \frac{1}{6} \cdot 90 = 10$$

- ▶ We can thus compute the hedging portfolio at each node

$$\begin{array}{rcl} & & x_3 = -80 \\ & & y_3 = 1 \\ & x_2 = -85/2 & \\ & y_2 = 95/120 & \\ x_1 = -55/2 & & x_3 = -5 \\ y_1 = 5/8 & & y_3 = 1/6 \\ & x_2 = -5/2 & \\ & y_2 = 1/8 & \\ & & x_3 = 0 \\ & & y_3 = 0 \end{array}$$

# General algorithm

- ▶ To develop a general binomial algorithm, we introduce some more notation to help us keep track of the price evolution
- ▶ From the procedure above, the value of the price process at time  $t$  is

$$S_t = su^k d^{t-k}, \quad k = 0, \dots, t$$

- ▶ The index  $k$  denotes the number of up-moves that have occurred
- ▶ Each node in the binomial tree is a pair  $(t, k)$  with  $k = 0, \dots, t$
- ▶ If  $V_t(k)$  denotes the value of the portfolio at the node  $(t, k)$ , then  $V_t(k)$  can be computed recursively by the scheme

$$V_t(k) = \frac{1}{1+R} \{q_u V_{t+1}(k+1) + q_d V_{t+1}(k)\}$$

$$V_T(k) = \Phi \left( su^k d^{T-k} \right)$$

# General algorithm

- ▶ The hedging portfolio is given by

$$x_t(k) = \frac{1}{1+R} \frac{uV_t(k) - dV_t(k+1)}{u-d}$$
$$y_t(k) = \frac{1}{S_{t-1}} \frac{V_t(k+1) - V_t(k)}{u-d}$$

- ▶ The arbitrage-free price at  $t = 0$  of a  $T$ -claim  $X$  is redefined as

$$\begin{aligned} \Pi(0; X) &= \frac{1}{1+R} [\Phi(u) \cdot q_u + \Phi(d) \cdot q_d] \\ &\quad \downarrow \\ \Pi(0; X) &= \frac{1}{(1+R)^T} \sum_{k=0}^T \binom{T}{k} q_u^k q_d^{T-k} \Phi(su^k d^{T-k}) \end{aligned}$$

- ▶ In the last formula,  $k$  has binomial distribution with coefficient

$$\binom{T}{k} = \frac{T!}{k!(T-k)!}$$

# General algorithm

- ▶ In our case, for  $T = 3$ :

- ▶  $k = 0$  occurs only in one way (always go down in the tree)

$$\binom{3}{0} = \frac{3!}{0!(3-0)!} = \frac{3 \cdot 2}{1 \cdot (3 \cdot 2)} = 1$$

- ▶  $k = 1$  occurs in three ways (go up in  $t = 1$ ,  $t = 2$ , or  $t = 3$ )

$$\binom{3}{1} = \frac{3!}{1!(3-1)!} = \frac{3 \cdot 2}{1 \cdot (2)} = 3$$

- ▶  $k = 2$  occurs in three ways (go down in  $t = 1$ ,  $t = 2$ , or  $t = 3$ )

$$\binom{3}{2} = \frac{3!}{2!(3-2)!} = \frac{3 \cdot 2}{2 \cdot (1)} = 3$$

- ▶  $k = 3$  occurs only in one way (always go up in the tree)

$$\binom{3}{3} = \frac{3!}{3!(3-3)!} = \frac{3 \cdot 2}{3 \cdot 2 \cdot (1)} = 1$$

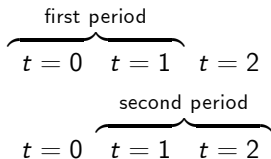
# Tree diagram in practice

- First task: create this matrix, using **time** and **stock moves** as inputs

		row col <i>val</i> (row, col)
	row col <i>val</i> (row, col)	
row col <i>val</i> (row, col)		row col <i>val</i> (row, col)
	row col <i>val</i> (row, col)	
		row col <i>val</i> (row, col)

# Time

- ▶  $N$  is the number of periods, so  $N + 1$  is the number of dates
- ▶  $t = 0, \dots, N$  indexes dates
- ▶ example:  $N = 2$  periods;  $N + 1 = 3$  dates



# Time

- ▶  $N$  governs both the total number of columns and rows

		row col <i>val</i> (row, col)
	row col <i>val</i> (row, col)	
row col <i>val</i> (row, col)		row col <i>val</i> (row, col)
	row col <i>val</i> (row, col)	
		row col <i>val</i> (row, col)

$N + 1$

$2N + 1$

# Stock moves

- ▶  $t = 0, \dots, N$  is also the number of total moves at date  $t$  (+1 per period)
- ▶ example: no moves at  $t = 0$ , one move at  $t = 1$ , two moves at  $t = 2$ ...
- ▶  $k = 0, \dots, t$  is the number of (possible) up-moves
- ▶  $t - k$  is the number of (possible) down-moves

# Stock moves

	2. 2nd column = "2nd" date $col = t + 1$ $\downarrow$	row col $val(row, col)$
1. first column = "first" date $col = t + 1$ $\downarrow$	row col $val(row, col)$	$\leftarrow$ 5. top filled row ( $k = t$ ) $k$ moves up from bottom $row = N + 1 + t - 2k$
row col $val(row, col)$	$\leftarrow$ 3. central row ( $2k = t$ ) $row = N + 1$	row col $val(row, col)$
	row col $val(row, col)$	$\leftarrow$ 4. bottom filled row ( $k = 0$ ) $t$ moves down from central $row = N + 1 + t$
		row col $val(row, col)$

# Columns

- ▶ Columns represent dates

$$\text{col} = \overbrace{t + 1}^{0 \text{ not recognized as column}}$$

- ▶ example 1:  $t = 0$  is the 1<sup>st</sup> date, so:  $\text{col} = t + 1 = 1$ , as in “1<sup>st</sup>”
- ▶ example 2:  $t = 1$  is the 2<sup>nd</sup> date, so:  $\text{col} = t + 1 = 2$ , as in “2<sup>nd</sup>”

# Rows

- ▶ Rows represent moves

$$\text{row} = \underbrace{\underbrace{N+1}_{\text{central row}} + \underbrace{t}_{\text{adds total moves}}}_{\text{finds bottom cell to fill in}} - \underbrace{2k}_{\substack{\text{links cell to up-moves} \\ 2\times \text{ to leave blank cell}}}$$

# Rows

- ▶ example:  $N = 2$ , so  $t = 0, 1, 2$
- ▶ example 1: if  $t = 0$ , then  $k = 0$ , so

$$\text{row} = N + 1 + t - 2k = 2 + 1 + 0 - 2 \cdot 0 = 3$$

- ▶ example 2: if  $t = 1$ , then  $k = 0, 1$ 
  - ▶ example 2a: if  $k = 0$ , then  $t - k = 1$  (down-move)

$$\text{row} = N + 1 + t - 2k = 2 + 1 + 1 - 2 \cdot 0 = 4$$

- ▶ example 2b: if  $k = 1$ , then  $t - k = 0$  (up-move)

$$\text{row} = N + 1 + t - 2k = 2 + 1 + 1 - 2 \cdot 1 = 2$$

- ▶ example 3: if  $t = 2$ ...

# Tree diagram filled-in

		$N + 1 + t - 2k \quad 1$ $t + 1 \quad 3$ $val(1, 3)$
	$N + 1 + t - 2k \quad 2$ $t + 1 \quad 2$ $val(2, 2)$	
$N + 1 + t - 2k \quad 3$ $t + 1 \quad 1$ $val(3, 1)$		$N + 1 + t - 2k \quad 3$ $t + 1 \quad 3$ $val(3, 3)$
	$N + 1 + t - 2k \quad 4$ $t + 1 \quad 2$ $val(4, 2)$	
		$N + 1 + t - 2k \quad 5$ $t + 1 \quad 3$ $val(5, 3)$

# Stock value

- ▶ The value of the stock depends on the direction of the moves

$$val = \underbrace{s}_{\text{initial value}} \cdot \underbrace{u^k}_{\text{\# of up-moves}} \cdot \underbrace{d^{t-k}}_{\text{\# of down-moves}}$$

# Stock value

- ▶ example:  $N = 2$ , so  $t = 0, 1, 2$
- ▶ example 1: if  $t = 0$ , then  $k = 0$  and  $t - k = 0$ , so

$$val = s \cdot u^k \cdot d^{t-k} = s \cdot u^0 \cdot d^{0-0} = s$$

- ▶ example 2: if  $t = 1$ , then  $k = 0, 1$ 
  - ▶ example 2a: if  $k = 0$ , then  $t - k = 1$  (down-move)

$$val = s \cdot u^k \cdot d^{t-k} = s \cdot u^0 \cdot d^{1-0} = sd$$

- ▶ example 2b: if  $k = 1$ , then  $t - k = 0$  (up-move)

$$val = s \cdot u^k \cdot d^{t-k} = s \cdot u^1 \cdot d^{1-1} = su$$

- ▶ example 3: if  $t = 2...$

# Stock value

		$  \begin{array}{r}  N + 1 + t - 2k \quad 1 \\  t + 1 \quad 3 \\  s \cdot u^k \cdot d^{t-k} \quad su^2  \end{array}  $
	$  \begin{array}{r}  N + 1 + t - 2k \quad 2 \\  t + 1 \quad 2 \\  s \cdot u^k \cdot d^{t-k} \quad su  \end{array}  $	
$  \begin{array}{r}  N + 1 + t - 2k \quad 3 \\  t + 1 \quad 1 \\  s \cdot u^k \cdot d^{t-k} \quad s  \end{array}  $		$  \begin{array}{r}  N + 1 + t - 2k \quad 3 \\  t + 1 \quad 3 \\  s \cdot u^k \cdot d^{t-k} \quad sdu  \end{array}  $
	$  \begin{array}{r}  N + 1 + t - 2k \quad 4 \\  t + 1 \quad 2 \\  s \cdot u^k \cdot d^{t-k} \quad sd  \end{array}  $	
		$  \begin{array}{r}  N + 1 + t - 2k \quad 5 \\  t + 1 \quad 3 \\  s \cdot u^k \cdot d^{t-k} \quad sd^2  \end{array}  $

# Hedging portfolio

- ▶ The hedging portfolio is last composed at the last-but-one date, so the columns are  $N + 1 - 1 = N$
- ▶ We need two rows for each cell at that date, so the rows are  $2(2N + 1 - 2) = 2(2N - 1)$

## HEDGING PORTFOLIO: VALUES (POSITION)

$$\begin{aligned} \text{row} &= \overbrace{2N - 1}^{\text{central row}} + \overbrace{2t}^{\text{finds bottom cell to fill in} \\ \text{adds total moves}} - \overbrace{4k}^{2 \times \text{to leave blank cell} \\ \text{links cell to up-moves}} \\ &= 2(N + t - 2k) - 1 \end{aligned}$$

# Hedging portfolio

## HEDGING PORTFOLIO: VALUES (LINKS)

hedging portfolio

$$x: (2(N + t - 2k) - 1, t + 1)$$

$$y: (2(N + t - 2k), t + 1)$$



option value

$(N + t - 2k, t + 2)$
$(N + 2 + t - 2k, t + 2)$

- We write the values for  $x$  and  $y$  as in the model

# MATLAB codes

- ▶ `BT_StockTree.m`
- ▶ `BT_EurCallTree.m`
- ▶ `BT_EurCallHP.m`

**Exercise** Create the MATLAB codes for a European put option

# Table of contents

1. Basic risk management strategies
2. Binomial model
3. Multiperiod binomial model
- 4. Discrete-time options**
5. Classical hedging strategies
6. Continuous-time options

# Calibration

- ▶ For practical use, the binomial model needs *calibration*
- ▶ Calibration expresses the model's parameter as functions of observables
- ▶ Practitioners only observe a limited amount of information
  - ▶ e.g. current value of  $S_t$ , its trend and volatility, interest rate  $R$
  - ▶ they do not observe  $u$  and  $d$ , or  $q_u$  and  $q_d$
- ▶ We thus need to infer some values from the available information
- ▶ The CRR (Cox, Ross and Rubinstein) is a widely used calibration

$$u = e^{\sigma\sqrt{\delta t}}, \quad d = e^{-\sigma\sqrt{\delta t}}, \quad q_u = \frac{e^{r\delta t} - d}{u - d}$$

- ▶  $\sigma$  indicates the variability of the underlying stock
- ▶  $\delta t$  is the length of the time interval considered
- ▶  $r$  is the constant deterministic interest rate

# Calibration

- ▶ The parameterization uses the exponential version of interest rate
  - ▶ this makes no difference since we can freely switch between the two versions by using the approximation

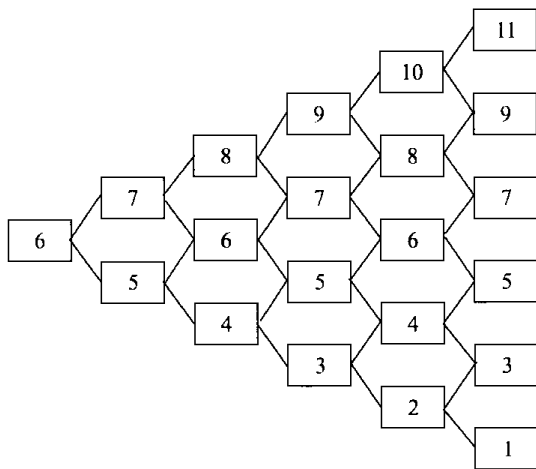
$$1 + r \simeq e^r$$

- ▶ note also that  $d = 1/u$ , thus the resulting tree is recombining
- ▶ We also need increasing the number of state that we consider
  - ▶ the model is of no practical use if only a few states are allowed
  - ▶ to do so, we let trade occur at intermediate dates before maturity
  - ▶ this is not only practical, but also essential at times (e.g. when we want to price American options)
- ▶ MATLAB code (function): `BTC_EurCallHP.m` (`BT_Calib`)

# Faster codes

- ▶ The implementation of binomial tree can be improved
  - ▶ no need to repeat calculation of discounted probabilities in the 'for' loop; we can multiply discount factor and probabilities once
  - ▶ with CRR calibration ( $ud = 1$ ), we may save memory by storing the underlying asset prices in a vector rather than a matrix
- ▶ Considering  $N$  time-steps, we store  $2N + 1$  elements rather than  $N^2$ 
  - ▶ for five periods, only eleven different values are used for the underlying asset price, down from 25 elements
  - ▶ with greater accuracy, e.g.  $N = 1000$ , the contrast is between (one-million-element) matrix and (2001-entry) vector becomes huge

# Tree-diagram computational strategy



# Tree-diagram computational strategy

- ▶ The numbers shown there are locations in the vector
  - ▶ element 1 stores the lowest value (down-steps only)
  - ▶ odd-numbered entries correspond to the last time-layer
  - ▶ even-numbered entries correspond to the second-to-last time-layer
  - ▶ the tree's root may be even-numbered or odd-numbered, depending on the number of time steps
- ▶ The same scheme may be adopted to store option values
- ▶ In principle, we should use two vectors corresponding to two consecutive time layers
- ▶ However, we may use one vector of  $2N + 1$  elements since
  - ▶ even-numbered elements belong to a layer
  - ▶ odd-numbered elements belong to another one

# Computational strategies' outcome comparison

MATLAB codes

- ▶ `BTC_EurOptions.m`
- ▶ `BTS_EurOptions.m`
- ▶ `BT_EurOptions_Cfr.m`

# Pricing derivatives with the binomial model

## **I. Pay-later options**

II. American options

III. Spread options

# Pricing a pay-later option

- ▶ Consider a pay-later call option on a non-dividend-paying stock
  - ▶ the key feature of the pay-later option is that no premium is paid up-front, when the contract is entered
  - ▶ under certain conditions, it will be paid later instead
- ▶ If the option is in the money at expiration, then the option *must* be exercised and a *premium* is paid to the writer
  - ▶ otherwise, the option expires worthless and no premium is due
  - ▶ the net payoff for the option holder can be negative:
    - ▶ if the option is not deeply in the money
    - ▶ then the payoff may be smaller than the premium
- ▶ By no-arbitrage argument, if the net payoff were always non-negative, we could not have a zero-value contract at  $t = 0$

# Pay-later premium

- ▶ How can we find the fair premium value?
- ▶ Given a premium  $M$ , the payoff will be

$$\Pi(S_T, M) = \begin{cases} S_T - K - M & \text{if } S_T \geq K \\ 0 & \text{if } S_T < K \end{cases}$$

- ▶ Given  $M$ , we may find the value of the option using a binomial model
- ▶ Now we must find a value  $M$  such that the risk-neutral expectation of the payoff, with respect to  $S_T$ , is zero

$$E^Q [\Pi(S_T, P)] = 0$$

- ▶ Provided that interest rate is constant over time, the discount factor does not play any role

# Pay-later option price

MATLAB codes

- ▶ To solve this equation for  $M$ , we couple the binomial tree with the numerical method to solve non-linear equations
- ▶ We first prepare a function returning the discounted payoff of the pay-later option, for a given  $M$
- ▶ Then, we solve for  $M$  using the pre-compiled function 'fzero' and a starting premium for the search
  
- ▶ `BTS_PayLaterCall.m` (BTS\_PLC)

**Exercise** Create MATLAB codes for a European pay-later put

# Pricing derivatives with the binomial model

I. Pay-later options

**II. American options**

III. Spread options

# Pricing an American put option

- ▶ Pricing an American option by the binomial tree technique that we have illustrated in the last section is fairly easy
- ▶ The only critical point is how we should account for early exercise
- ▶ We deal here with a vanilla American-style *put* option on a non-dividend paying stock
- ▶ What about pricing an American *call* option?
  - ▶ if the underlying security does not pay any dividend
  - ▶ and the risk-free interest rate is positive, i.e.  $B_t < 1 = B_T, \forall t < T$
  - ▶ then you should never exercise an American call option in advance
  - ▶ this means American and European call options have the same value

$$C_t^A = C_t^E, \forall t < T$$

# Why an American call is never exercised

A three-step argument

- i. The American call written on a financial asset that does not pay dividends provides for the additional right of early exercise
  - ▶ Hence, it cannot be valued less than its European counterpart

$$C_t^A \geq C_t^E, \forall t < T$$

- ii. The European call cannot be worth less than the difference between the current values of the financial asset and the strike price

$$C_t^E \geq S_t - K B_t, \forall t < T$$

# Why an American call is never exercised

A three-step argument

- ▶ Suppose

$$C_t^E < S_t - K B_t$$

- ▶ We can buy the call, sell the underlying,  $K B_t$  goes into the bank and the profit generated is

$$S_t - (C_t^E + K B_t) > 0$$

- ▶ At maturity, our position cannot be negative
  - ▶ if the call is exercised, the exercise price is covered by the bonds and our short position is neutralized

$$K - K B_T = 0 \text{ and } S_T - S_T = 0$$

- ▶ otherwise, the long position in bonds has greater value than the short position in the underlying, with the additional arbitrage profit

$$K - S_T > 0$$

# Why an American call is never exercised

A three-step argument

- ▶ Jointly considering the two conditions, it must then be

$$C_t^A \geq S_t - K B_t, \quad \forall t < T$$

- iii. Since by definition  $B_t < 1$ , early exercise would produce

$$S_t - K < S_t - K B_t, \quad \forall t < T$$

→ An active American call is worth more than its early exercise

$$C_t^A \geq S_t - K, \quad \forall t < T$$

- ▶ this holds true even if one believes that the value of the stock will fall below the value of  $K$
- ▶ in this case, the option should be sold rather than exercised

# American put at maturity

- ▶ Consider a node  $(i, N)$  on the last time layer of the tree diagram
- ▶ If the put is in the money, it is obviously optimal to exercise it
- ▶ Hence, at expiration we have

$$\Pi_{i,N} = \max \{K - S_{i,N}, 0\}$$

- ▶  $S_{i,N} = Su^i d^{N-i}$  is the underlying asset price on node  $(i, N)$

# American put before maturity

- ▶ Now consider a point in the second-to-last time layer
  - ▶ if the option is not in the money ( $S_{i,N-1} > K$ ), we do not exercise
  - ▶ if the option is in the money, we should wonder about the opportunity of taking an immediate profit  $K - S_{i,N-1}$
- ▶ In other words, we have to solve an **optimal stopping** problem

[en.wikipedia.org/wiki/Optimal\\_stopping](https://en.wikipedia.org/wiki/Optimal_stopping)

- ▶ at each time step, we must observe the state of a dynamic system
- ▶ decide whether we should stop the game and just grab the money
- ▶ or we should go onto the next step

# Optimal stopping

- ▶ We solve the problem in a simple way, comparing the immediate payoff (*intrinsic value*) against the *continuation value*
- ▶ Naturally, the intrinsic value is

$$\Pi_{i,N-1}^x = \max \{K - S_{i,N-1}, 0\}$$

- ▶ We exercise if the intrinsic value exceeds the continuation value

$$\Pi_{i,N-1}^c = e^{-r\delta t} [q \Pi_{i+1,N} + (1 - q) \Pi_{i-1,N}]$$

- ▶ Hence, the option value in each second-to-last time layer node is

$$\Pi_{i,N-1} = \max \left\{ K - S_{i,N-1}, e^{-r\delta t} [q \Pi_{i+1,N} + (1 - q) \Pi_{i-1,N}] \right\}$$

# American put price

MATLAB codes

- ▶ The same argument may be repeated recursively for any time layer
  - ▶ we start from the last time layer, where the option value is the payoff
  - ▶ we proceed backward in time using the slight modification of the usual discounted expectation scheme given above
  - ▶ specifically, we first compute the continuation value, then compare it against the intrinsic value
- ▶ MATLAB Financial Toolbox provides the function `binprice.m`
  - ▶ prices vanilla American puts and calls (allowing for dividends)
  - ▶ we may compare our result with that produced by this function
- ▶ `BTS_AmericanPut.m` (BTS\_AP)

# Pricing derivatives with the binomial model

I. Pay-later options

II. American options

**III. Spread options**

# Pricing a spread option

- ▶ What happens if the financial derivatives are written on more than one underlying asset?
- ▶ We extend the binomial model technique to multidimensional options and consider an American spread option on two assets
- ▶ The payoff (intrinsic value) of this option at (before) maturity is

$$\max \{S_1 - S_2 - K, 0\}$$

- ▶ The basic approach can be extended to more general options
  - ▶ we generalize it by considering continuous dividend yields  $(e_1, e_2)$
  - ▶ this is easily done as we need only adjust the risk-neutral dynamics

# Spread option calibration

- ▶ Calibration yields the following move factors and probabilities

$$u_1 = e^{\sigma_1 \sqrt{\delta t}} \quad d_1 = 1/u_1$$

$$u_2 = e^{\sigma_2 \sqrt{\delta t}} \quad d_2 = 1/u_2$$

$$p_{uu} = \frac{1}{4} \left[ 1 + \sqrt{\delta t} \left( \frac{\mu_1}{\sigma_1} + \frac{\mu_2}{\sigma_2} \right) + \rho \right]$$

$$p_{ud} = \frac{1}{4} \left[ 1 + \sqrt{\delta t} \left( \frac{\mu_1}{\sigma_1} - \frac{\mu_2}{\sigma_2} \right) - \rho \right]$$

$$p_{du} = \frac{1}{4} \left[ 1 - \sqrt{\delta t} \left( \frac{\mu_1}{\sigma_1} - \frac{\mu_2}{\sigma_2} \right) - \rho \right]$$

$$p_{dd} = \frac{1}{4} \left[ 1 - \sqrt{\delta t} \left( \frac{\mu_1}{\sigma_1} + \frac{\mu_2}{\sigma_2} \right) + \rho \right]$$

- ▶ The first (second) probability subscript refers to an asset 1 (2) move
- ▶  $\mu$  and  $\sigma$  capture the asset price trend and volatility
- ▶  $\rho$  is the price correlation between the two assets

# Probability interpretation

- ▶ These conditions have an intuitive interpretation
- ▶ Two up-moves probability is large when the two drifts are large (relative to the respective volatilities) and correlation is positive
- ▶ In the probability of a  $S_1$ -up-move and a  $S_2$ -down-move
  - ▶ the drift  $\mu_2$  has a negative impact (the larger the drift, the less likely a down-move)
  - ▶ while negative correlation makes this joint movement more likely
- ▶ A similar reasoning applies to a  $S_1$ -down-move and a  $S_2$ -up-move
- ▶ Two up-moves probability is smaller when drifts are large and is larger when correlation is positive

# Spread option price

MATLAB codes

- ▶ The implementation of this bidimensional model really requires careful memory management
- ▶ Since each asset's move are the same in absolute value, we may once again resort to vectors rather than matrices
- ▶ The prices of the options are stored in a matrix instead, and initialized with the option payoffs
- ▶ Since the options are American, we compute the continuation values as a risk-neutral expectation
- ▶ We then compare them against the respective intrinsic values
- ▶ `BTS_AmericanSpread.m` (BTS\_AS)

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4. Discrete-time options
- 5. Classical hedging strategies**
6. Continuous-time options

# Numerical simulation

- ▶ A great deal of financial concepts builds on *continuous-time* pricing
- ▶ Continuous-time computations involve complex **definite integrals**: some can be algebraically solved, others cannot

[en.wikipedia.org/wiki/Integral](https://en.wikipedia.org/wiki/Integral)

- ▶ Numerical simulation helps in addressing this issue when integrals cannot be solved algebraically in any obvious way
- ▶ A function's definite integral is a number: calculating this number is a deterministic problem that has nothing to do with stochasticity
- ▶ However, the involved computations can be perceived as part of a stochastic context by interpreting the integral as an *expected value*

# Integrals and the law of large numbers

- ▶ For example, consider an integral defined on the unit interval  $[0, 1]$

$$I = \int_0^1 g(x) dx$$

- ▶ We can interpret this integral as the expected value  $E[g(x)]$ , with  $x \sim U(0, 1)$  a uniform random variable defined on the interval  $(0, 1)$
- ▶ We may estimate the expected value (a number) with a sample mean (a random variable)

# Integrals and the law of large numbers

- ▶ We generate a sequence  $\{x_i\}$  of independent random draws from the uniform distribution, then compute the sample mean

$$\hat{l}_m = \frac{1}{m} \sum_{i=1}^m g(x_i)$$

- ▶ The **law of large numbers** then implies, with certainty

[en.wikipedia.org/wiki/Law\\_of\\_large\\_numbers](https://en.wikipedia.org/wiki/Law_of_large_numbers)

$$\lim_{m \rightarrow \infty} \hat{l}_m = l$$

# Monte Carlo simulation

- ▶ A well-established simulation approach is the **Monte Carlo method**

[en.wikipedia.org/wiki/Monte\\_Carlo\\_method](https://en.wikipedia.org/wiki/Monte_Carlo_method)

- ▶ the name “Monte Carlo” is attributed to Nicholas C. Metropolis
  - ▶ he linked the random sampling to the activity of the well-known casino located in the Principality of Monaco
- ▶ The method *mimics* random sampling
  - ▶ it is factually impossible to perform random sampling on computers
  - ▶ but we can use a sequence of **pseudo-random** numbers, created by special *generators* as provided by most programming languages

[en.wikipedia.org/wiki/Pseudo-random\\_number\\_sampling](https://en.wikipedia.org/wiki/Pseudo-random_number_sampling)

# Monte Carlo simulation

## MATLAB commands

- ▶ For instance, we may consider the integral

$$I = \int_0^1 e^x dx = [e^x]_0^1 = e - 1 \cong 1.7183$$

- ▶ In order to generate random sampling from a uniform distribution, we can use the MATLAB `rand` function
  - ▶ the `rand(m,n)` command produces an  $m \times n$  matrix of random extractions from a uniform distribution
  - ▶ it should be noted that the parameters  $m$  and  $n$  have nothing to do with the distribution, which merely is  $U(0,1)$
- ▶ The estimates reliability varies according to the sample size
  - ▶ to have a reproducible experiment: `rand('state',0)`
  - ▶ we average over 10 extractions: `mean(exp(rand(1,10)))`
  - ▶ and over one million extractions: `mean(exp(rand(1,1000000)))`
  - ▶ the estimate is not very reliable for a few extractions, but gets closer to the correct number with more extractions

# European call option continuous-time pricing

- ▶ Specifically, we are interested in pricing derivatives, for instance a European call option
- ▶ Continuous-time pricing also involves the calculation of a risk-neutral valuation formula of the derivative's payoff

$$F(t, s) = e^{-r(T-t)} E_{t,s}^Q [\Phi(S(T))]$$

- ▶ Depending on the type of derivative, we may need to generate
  - ▶ the entire sample paths of the underlying value
  - ▶ simply the price of the asset at maturity
- ▶ The generation of entire paths will be covered later
- ▶ A European call option requires sampling the payoff only

$$\Phi(S(T)) = \max\{S(T) - K, 0\}$$

# European call option continuous-time pricing

- ▶ In the continuous-time model, the underlying's price at maturity is

$$S(T) = s e^{(r - \sigma^2/2)(T-t) + \sigma[\bar{W}(T) - \bar{W}(t)]}$$

- ▶  $\bar{W}(T) - \bar{W}(t)$  is the **Wiener process** innovation between  $t$  and  $T$
- ▶ Wiener process innovations are normally distributed with zero mean and variance equal to the time interval,  $T - t$
- ▶ the innovation sampling equals an extraction from a standardized normal random variable,  $\varepsilon \sim N(0, 1)$  multiplied by the value  $\sqrt{T - t}$

[en.wikipedia.org/wiki/Wiener\\_process](http://en.wikipedia.org/wiki/Wiener_process)

- ▶ Our pricing equation therefore becomes

$$F(t, s) = e^{-r(T-t)} E_{t,s}^Q \left[ \max \left\{ s e^{(r - \sigma^2/2)(T-t) + \sigma \varepsilon \sqrt{T-t}} - K, 0 \right\} \right]$$

- ▶ MATLAB code (function): `AE_EurCall.m` (`AE_EC`)

# Precision of continuous-time pricing

- ▶ Clearly, to obtain sufficiently robust results, we should not refer to a simple point estimate
- ▶ We should also calculate some confidence intervals for the estimate
- ▶ Ideally, we should understand how many extractions are needed to achieve a certain precision
- ▶ In general, many extractions seem to be needed, especially if
  - ▶ the underlying asset is very volatile
  - ▶ the option value depends on the entire underlying price process
- ▶ The number of draws could then become prohibitive to manage
- ▶ In sum, we need clever ways to reduce the variance of the estimator

# Simulation of the underlying price process

- ▶ The application of Monte Carlo methods to derivative pricing builds on generating sample paths of the underlying price process
- ▶ We've just seen that pricing European options needs only computing the price of the underlying asset at maturity
- ▶ But if the derivative depends on the time path of the underlying price process, then we theoretically need to know the whole path
- ▶ In practical terms, however, we may simply generate a sequence of values that the underlying takes at certain instants of time
- ▶ After all, numerical simulation software works with a discrete number of elements
- ▶ We must therefore carry out a *time discretization* of the model

# Time discretization and price process

- ▶ The simplest approach to time discretization is the **Euler method**

[en.wikipedia.org/wiki/Euler\\_method](https://en.wikipedia.org/wiki/Euler_method)

- ▶ We choose a discrete interval of time, denoted by  $\delta$
- ▶ We generate a draw  $\varepsilon \sim N(0, 1)$  at each instant of time which define these intervals
- ▶ We write the process that we need to discretize as a function of these draws
- ▶ For financial assets, the relevant process is the **geometric Brownian motion**, here expressed in integral form on the interval  $(t, t + \delta)$

$$S(t + \delta) = S(t) e^{(r - \sigma^2/2)\delta + \sigma[\bar{W}(t + \delta) - \bar{W}(t)]}$$

[en.wikipedia.org/wiki/Geometric\\_Brownian\\_motion](https://en.wikipedia.org/wiki/Geometric_Brownian_motion)

# The geometric Brownian motion

- ▶ Recall that a Wiener process innovation is a normal random variable with zero mean and variance equal to the time interval length

$$\bar{W}(t + \delta) - \bar{W}(t) \sim N(0, \delta) \equiv \sqrt{\delta} \cdot N(0, 1)$$

- ▶ We may build on our draw-generating process to obtain

$$\sqrt{\delta} \varepsilon \sim N(0, \sqrt{\delta})$$

- ▶ Therefore, we can rewrite the geometric Brownian motion as

$$S(t + \delta) = S(t) e^{(r - \sigma^2/2)\delta + \sigma\sqrt{\delta}\varepsilon}$$

- ▶ MATLAB code (function): `AE_GraphStockSim.m` (AE)

# Dynamic risk management

- ▶ We now turn to consider dynamic risk-management strategies based on a portfolio's **Greeks**

[en.wikipedia.org/wiki/Greeks\\_\(finance\)](https://en.wikipedia.org/wiki/Greeks_(finance))

- ▶ The most popular Greeks are *delta* (sensitivity to underlying's price) and *gamma* (sensitivity to underlying's price volatility)
- ▶ We use **delta-hedging** to exemplify the strategy, but analogous schemes can be based upon all the other Greeks

[en.wikipedia.org/wiki/Delta\\_neutral](https://en.wikipedia.org/wiki/Delta_neutral)

- ▶ A strategy may also involve more than one Greek
- ▶ Once the strategy is implemented, the portfolio is said to be *neutral* with respect to the relevant Greek(s)

# Definition of delta hedging

- ▶ Delta hedging consists of composing a portfolio whose value remains unchanged when small changes occur in the value of the underlying
- ▶ The delta of a portfolio is the derivative of its value with respect to the price of the underlying

$$\Delta^P = \frac{\partial V_t^P}{\partial s}$$

- ▶ If  $\Delta^P = 0$ , then the portfolio is *delta-neutral* (around a given underlying's value  $s$ )
- ▶ If  $\Delta^P \neq 0$ , then we may obtain neutrality:
  - ▶ by selling the portfolio and investing the resulting resources in bonds
  - ▶ by modifying the portfolio composition (buying or selling units of underlying/derivative)

# Implementation of delta hedging

- ▶ The value of any security based on a given underlying is correlated with the price of that underlying
- ▶ We can therefore *rebalance* the portfolio composition so that the *resulting* portfolio is delta-neutral
  - ▶ let  $V^z(t, s)$  denote the value of the generic security  $z$  at time  $t$ , expressed as a function of the price  $s$  of the underlying
  - ▶ let  $x$  denote the units of the security added to the portfolio
- ▶ The value of the rebalanced portfolio  $p'$  is

$$V^{p'}(t, s) = V^p(t, s) + x \cdot V^z(t, s) \quad (2)$$

- ▶ For  $p'$  to be delta-neutral, we choose  $x$  such that  $\partial V^{p'} / \partial s = 0$

$$\frac{\partial V^p}{\partial s} + x \frac{\partial V^z}{\partial s} = 0$$

- ▶ Utilizzando the definition of delta, the solution is

$$x = -\frac{\Delta_p}{\Delta_z} \quad (3)$$

## Example: delta hedging of a derivative

- ▶ Suppose to have a short position in a derivative  $g$  with price process  $V^g(t, s)$
- ▶ We want to hedge the risk of this transaction using the underlying
- ▶ In order to apply (2), we substitute  $V^p = -V^g$  and  $z = s$

$$\frac{\partial}{\partial s} (-V^g + xs) = 0$$

- ▶ The solution is

$$x = \frac{\partial V^g(t, s)}{\partial s} = \Delta_g$$

- ▶ The delta of a derivative gives us the units of underlying necessary to hedge the derivative

# Delta hedging in practice

- ▶ Hedging the derivatives amounts to dismissing the risk that the assumed position involves
- ▶ It should then come as no surprise that it is possible to show an option price is essentially the cost of a delta hedging strategy
- ▶ We can write a MATLAB code to estimate the average cost of a delta hedging strategy
- ▶ We need to produce an array of sample paths, generated by a specific function (for example,  $\Delta E$ )
- ▶ In this case, unlike the evaluation of the option, the actual underlying's trend must be used in the simulation
- ▶ To purchase units of underlying, we may resort to a loan
  - ▶ since the interest rate is deterministic and constant, we simply record the cash flows necessary for the negotiations
  - ▶ we then discount the cash flows at time  $t = 0$

# Delta hedging in practice

- ▶ The number of underlying units to be held in the portfolio is given by the option delta
- ▶ We calculate the delta with the `blsdelta` function for each point of the sample path
- ▶ We then compare compare the cost of the delta hedging strategy with the price of the option
- ▶ To simplify matter, we compute the option price using the built-in MATLAB function (`blsprice`)
- ▶ MATLAB code (function): `AE_DeltaHedging.m` (`AE_DH`)

# Definition of stop-loss

- ▶ A strategy providing linear coverage as the delta hedging but easier to implement is the so-called *stop-loss*
- ▶ With reference to a European call option, the strategy consists of the following elements
  - ▶ a hedged position (hold a unit of underlying) when the price of the underlying is greater than the strike price (the option is in the money)
  - ▶ otherwise (the option is out of the money) one should opt for an uncovered position (hold no underlying unit)
- ▶ We should therefore buy a unit (if we do not already own it) when the price of the underlying rises above the strike price
- ▶ We sell the unit (if we own it) when it falls below the strike price

# Implementation of stop-loss

- ▶ This strategy is very intuitive, but it is not easy to implement consistently in continuous time
- ▶ However, we can evaluate its performance in the discrete, simulating it with the Monte Carlo method
- ▶ The problem in this case is that we cannot buy or sell the underlying at the exact strike price
  - ▶ we buy at a price greater than  $K$ , as soon as we find out that the price is higher than that strike price
  - ▶ for the same reason, we sell at a price slightly lower than  $K$
- ▶ Thus, even without considering transaction costs, there is a potential problem with the stop-loss strategy

# Stop-loss in practice

- ▶ We can estimate the average cost of a stop-loss strategy as follows
- ▶ We use a *covered* status indicator to detect when the underlying is higher or lower than the strike price
- ▶ We record a cashflow every time we buy or sell the underlying
  - ▶ if the value of the underlying is higher than the strike price at maturity, the holder will exercise the option
  - ▶ therefore the strike price received must be added to the cashflows
- ▶ Cashflows are negative when we buy the underlying and positive when we sell
- ▶ As a result, the cost of the strategy is valued as the average of the total discounted cashflows with inverted sign
- ▶ MATLAB code (function): `AE_StopLoss.m` (`AE_SL`)

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# Multidimensional options

- ▶ The Monte Carlo method is easily adapted to multidimensional options
- ▶ For illustrative purposes, we consider a European exchange option written on two assets
- ▶ The risk-neutral asset value process follows a two-dimensional geometric Brownian motion

$$dU(t) = rU(t) dt + \sigma_U U(t) dW_U(t)$$

$$dV(t) = rV(t) dt + \sigma_V V(t) dW_V(t)$$

- ▶ We assume the Wiener processes have instantaneous correlation  $\rho$

# Definition of exchange option

- ▶ The payoff of the option at maturity  $T$  is

$$\max(V(T) - U(T), 0)$$

- ▶ We can note that this option is a particular case of a spread option, whose payoff depends on the assets' price differential
- ▶ It is called exchange because it allows you to exchange one activity for another at maturity
- ▶ For example, if we hold a portfolio comprising  $U$  and an exchange option, the payoff at maturity is

$$U(T) + \max(V(T) - U(T), 0) = \max(U(T), V(T))$$

# Exact pricing of an exchange option

- ▶ For this option there exists an *analytical* evaluation formula based on a generalization of the Black-Scholes formula

$$P = V_0 N(d_1) - U_0 N(d_2)$$

- ▶ the values of the Gaussian cumulative distribution are

$$d_1 = \frac{\ln(V_0/U_0) + \hat{\sigma}^2 T/2}{\hat{\sigma}\sqrt{T}}$$

$$d_2 = d_1 - \hat{\sigma}\sqrt{T}$$

- ▶ the volatility of the option is given by

$$\hat{\sigma} = \sqrt{\sigma_V^2 + \sigma_U^2 - 2\rho\sigma_V\sigma_U}$$

- ▶ We write a MATLAB function (`exchange`) to implement the formula

# Correlated Wiener processes

- ▶ We discuss another issue before applying the Monte Carlo method
- ▶ We impose that the joint sampling of the paths generated by the related Wiener processes has a normal multivariate distribution
- ▶ To this end, we carry out a **Cholesky decomposition** of the covariance matrix

[en.wikipedia.org/wiki/Cholesky\\_decomposition](https://en.wikipedia.org/wiki/Cholesky_decomposition)

- ▶ we write the correlation matrix, with correlation coefficient  $\rho$

$$\Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

- ▶ we impose  $\Sigma = \mathbf{L}\mathbf{L}'$ , and obtain that the factors generating  $\Sigma$  are

$$\mathbf{L} = \begin{bmatrix} 1 & 0 \\ \rho & \sqrt{1-\rho^2} \end{bmatrix}$$

# Correlated Wiener processes

- ▶ It is easy to verify that the definition of  $\mathbf{L}$  obeys the identity

$$\begin{aligned}\mathbf{L}\mathbf{L}' &= \begin{bmatrix} 1 & 0 \\ \rho & \sqrt{1-\rho^2} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ 0 & \sqrt{1-\rho^2} \end{bmatrix} \\ &= \begin{bmatrix} 1 \cdot 1 + 0 \cdot 0 & 1 \cdot \rho + 0 \cdot \sqrt{1-\rho^2} \\ \rho \cdot 1 + 0 \cdot \sqrt{1-\rho^2} & \rho \cdot \rho + \sqrt{1-\rho^2} \cdot \sqrt{1-\rho^2} \end{bmatrix} \\ &= \begin{bmatrix} 1 & \rho \\ \rho & \rho^2 + 1 - \rho^2 \end{bmatrix} = \Sigma\end{aligned}$$

- ▶ The two related Wiener processes are then generated by two *independent* normal random variables,  $Z_1$  and  $Z_2$

$$\begin{aligned}\varepsilon_1 &= Z_1 \\ \varepsilon_2 &= \rho Z_1 + \sqrt{1-\rho^2} Z_2\end{aligned}$$

# Exchange option in practice

- ▶ In the case of the exchange option, we need to simply generate the joint sampling of the prices of the two assets at maturity
- ▶ After introducing the function, we calculate the values of the two related Wiener processes, a pair for each simulation
- ▶ The resulting vectors are used to compute the sample values at maturity of the geometric Brownian motions
- ▶ We then calculate the current values of the sample payoffs of the exchange option
- ▶ We also calculate the sample mean and its 95% confidence interval
- ▶ MATLAB code (function): `AE_Exchange.m` (`AE_EX`)

# Definition of barrier option

- ▶ We now turn to consider an option whose valuation depends on the time path followed by the value of the underlying
- ▶ The **barrier option** is one type of **exotic option**

[en.wikipedia.org/wiki/Barrier\\_option](https://en.wikipedia.org/wiki/Barrier_option)

[en.wikipedia.org/wiki/Exotic\\_option](https://en.wikipedia.org/wiki/Exotic_option)

- ▶ it activates ('*in*' type) or extinguishes ('*out*' type) if the price of the underlying reaches a predetermined level (the **barrier**)
  - ▶ the barrier can be placed above ('*up*' type) or below ('*down*' type) of the initial price of the underlying
  - ▶ there are therefore four main types of barrier options: *up-and-out*, *down-and-out*, *up-and-in*, and *down-and-in*
- ▶ An activated or extinguished option remains such even if the price of the underlying crosses the barrier again

# Down-and-out put option

- ▶ Barrier options are based on ordinary options, such as American, Bermudan, or European call or put option

[en.wikipedia.org/wiki/Option\\_style](http://en.wikipedia.org/wiki/Option_style)

- ▶ We examine here a European “down-and-out” put option
- ▶ The barrier is controlled at the end of each trading day
- ▶ There exists an analytical formula for continuous monitoring, which can be adjusted to reflect discrete monitoring
- ▶ As before, we use this formula to check the result of the simulation obtained with the Monte Carlo method

# Adjustment of analytic formula to discrete-time pricing

- ▶ When computing the exact valuation of the option, the barrier value must be corrected by the expression

$$\hat{S}_b = S_b e^{-0.5826 \cdot \sigma \sqrt{\delta}}$$

- ▶ The analytic formula refers to continuous-time monitoring
- ▶ Under discrete-time monitoring, a down-and-out option will get a higher valuation than in continuous-time monitoring
- ▶ The reason is that crossing the barrier is less likely

# Adjustment of analytic formula to discrete-time pricing

- ▶ In the (approximate) correction applied in the code
  - ▶ the term 0.5826 derives from the **Riemann zeta function**  
[en.wikipedia.org/wiki/Riemann\\_zeta\\_function](https://en.wikipedia.org/wiki/Riemann_zeta_function)
  - ▶  $\delta$  is the time interval between two consecutive monitoring instants
- ▶ The sign of the correction depends on the type of option
- ▶ For a down-and-out option, the sign is *minus* so that the artificially lower barrier reflects the lower barrier-crossing probability

# Barrier option in practice

- ▶ We implement the Monte Carlo simulation for the evaluation of a down-and-out put option as follows
- ▶ A parameter is used to determine how many times the price of the underlying should be compared with the barrier
- ▶ The payoff is zero if the price crosses the barrier at least once
  - ▶ the code simulates the complete path, though part of it may actually be useless if the barrier is crossed
  - ▶ nevertheless, this allows to streamline the implementation by refraining from using loops
- ▶ We also compute the number of paths in which the barrier is crossed
- ▶ MATLAB code (function): `AE_DownAndOut.m` (`AE_DO`)

# Definition of Asian option

- ▶ An Asian option payoff is a function of the average price of the underlying asset in a certain period of time

[en.wikipedia.org/wiki/Asian\\_option](https://en.wikipedia.org/wiki/Asian_option)

- ▶ For this reason, it is also called an average value option
- ▶ There are several variations, the most basic being
  - ▶ *fixed* strike price: the average value of the underlying defines the amount of resources due *to* the option holder
  - ▶ *floating* strike price: the average value of the underlying defines the strike price due *by* the option holder
- ▶ The average can be calculated in many ways
  - ▶ conventionally, it refers to an *arithmetic* mean
  - ▶ but Asian options with a *geometric* mean are also relatively popular

[en.wikipedia.org/wiki/Geometric\\_mean](https://en.wikipedia.org/wiki/Geometric_mean)

# Geometric Asian option

- ▶ We consider an Asian call option with geometric mean and fixed strike price calculated at discrete intervals of time
- ▶ The option payoff is

$$\max \left( \left[ \prod_{t=1}^N S(t) \right]^{\frac{1}{N}} - K, 0 \right)$$

- ▶ We assume that  $T$  is the maturity date of the option
- ▶ the index  $t$  is the progressive value of the intervals  $\delta = T/N$  between the beginning of the contract and the  $t^{\text{th}}$  monitoring
- ▶ For simplicity, we assume that monitoring is carried out at equidistant dates (although this is not always the case)

# Asian option in practice

- ▶ To apply the Monte Carlo method
  - ▶ we simply generate sample paths of the price of the underlying asset
  - ▶ we obtain, as usual, the sample mean of the discounted payoff
- ▶ A parameter represents the number of monitoring instant sampled to calculate the arithmetic mean
- ▶ It should not be confused with the number of simulations
- ▶ We compare the result with an exact evaluation formula
  
- ▶ MATLAB code (function): `AE_AsianGeomFixed.m` (`AE_AGF`)