### Valuation and Risk Management

#### Christoph Hambel

#### Tilburg University Tilburg School of Economics and Management Department of Econometrics and Operations Research

#### Fall Term 2023



School of Economics and Management

# Course Information



- Lecturers:
  - Christoph Hambel (financial modeling and derivative pricing)
  - Nikolaus Schweizer (numerical methods and risk measures) Henh Keffort (K. R. F. Keffort @ Albryundrudy - edu)
- This course ...
  - ... provides an introduction to financial modeling, pricing, and risk management beyond the Black-Scholes framework
  - ... requires some knowledge from mathematics and finance, especially from stochastic calculus (Wiener process, Itô's Lemma, Change of measure, Girsanov's Theorem, ...)
  - ... contains a guest lecture by (tba)
- Grading:
  - Exam 70%
  - Two Assignments (15% each)



- What can you expect from us? We will...
  - ... timely provide the learning material on Canvas
  - ... also upload the slides with hand-written complements (some slides are intentionally blank)
  - ... illustrate the lecture by examples
  - ... provide problem sets and a sample exam to practice the material
  - ... be available for questions
  - ... offer a virtual Q&A session after the last lecture
- What will we expect from you? You should ...
  - ... be well-prepared when you come to the lecture
  - ... actively participate in the lecture
  - ... take the opportunity and ask us questions during the classes

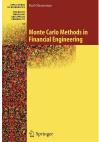
# Recommended Literature



- We do not make any book the *mandatory* reading for this course. However, we highly recommend the following textbooks:
  - Schumacher, J.M.: Introduction to Financial Derivatives: Modeling, Pricing and Hedging (Open Press TiU)
  - Björk, T.: Arbitrage Theory in Continuous Time (Oxford)
  - Glasserman, P.: *Monte-Carlo Methods in Financial Engineering* (Springer)
- This course follows the notation in Schumacher (2020), which contains a lot of exercises.







Christoph Hambel (TiSEM)

Valuation and Risk Management

Fall Term 2023

4 / 259

# TILBURG

#### Please notice that the plan can change!

- Mon, 28.08.2023, 12:45, WZ105 stude
- Mon, 04.09.2023, 12:45, WZ105
- Tue, 05.09.2023, 14:45, CUBE 218
- Mon, 11.09.2023, 12:45, WZ105
- Mon, 18.09.2023, 12:45, WZ105
- Tue, 19.09.2023, 14:45, CUBE 218
- Mon, 25.09.2023, 12:45, WZ105
- Mon, 02.10.2023, 12:45, WZ105
- Tue, 03.10.2023, 14:45, CUBE 218
- Mon, 09.10.2023, 12:45, WZ105
- Tue, 10.10.2023, 14:45, CUBE 218

Stides 1-22.



Introduction to Financial Modeling

- Discrete vs. Continuous Time Modeling
- Fundamentals from Stochastic Calculus
- Ontinuous time: Generic State Space Model
  - Framework
  - No Arbitrage and the First FTAP
  - The Numéraire-dependent Pricing Formula
  - Replication and the Second FTAP
  - The PDE Approach
- Ontingent Claim Pricing
  - Black-Scholes Revisited
  - Option Pricing in Incomplete Markets
  - Models with Dividends



#### Fixed Income Modeling

- Bonds and Yields
- Interest Rates and Interest Rate Derivatives
- Short Rate Models for the TSIR
- Empirical Models
- The Heath-Jarrow-Morton Framework
- LIBOR Market Model and Option Pricing
- A Brief Introduction to Credit Risk
  - Reduced-Form Modeling
  - Merton's Firm Value Model

# Part I

# Introduction to Financial Modeling



#### 1 Discrete vs. Continuous Time Modeling

#### 2 Fundamentals from Stochastic Calculus



Time

• Discrete time with time horizon T:

• Continuous time as a limit of discrete time  $(\Delta t \to 0 \text{ as } n \to \infty)$ :  $t \in [0, T]$ 



• Risk-free asset (bond) paying a constant interest rate:

$$B_{t+\Delta t} = B_t(1+r) \Delta t) \qquad \Longleftrightarrow \qquad \frac{\Delta B_{t+\Delta t}}{B_t} = r \cdot \Delta t$$

• Risky asset (stock):  

$$S_{t+\Delta t} = S_t (1 + \mu) \cdot \Delta t + \sigma \cdot \nu_{t+\Delta t} \cdot \sqrt{\Delta t}), \qquad \nu_{t+\Delta t} \sim i.i.d. (0,1)$$
• Return:  

$$\frac{\Delta S_{t+\Delta t}}{\sigma_t} = \mu \cdot \Delta t + \sigma \cdot \nu_{t+\Delta t} \cdot \sqrt{\Delta t}$$

**Problem:** Returns are not necessarily bounded from below by -1 and thus asset prices can be negative.

## Log Returns



• Way out?  $\rightarrow$  Model log returns,  $L_t$ , and take the exponential:

$$> S_{t+\Delta t} = S_t \mathrm{e}^{\Delta L_{t+\Delta t}}$$

• Risk-free asset (bond):

$$B_{t+\Delta t} = B_t e^{r \cdot \Delta t} \iff r \Delta t = \ln\left(\frac{B_{t+\Delta t}}{B_t}\right) = \Delta \ln B_{t+\Delta t}$$
  
• Risky asset (stock):  

$$\Delta L_{t+\Delta t} = \ln(S_{t+\Delta t}) - \ln(S_t) = \left(\mu - \frac{1}{2}\sigma^2\right)\Delta t + \sigma \cdot \nu_{t+\Delta t} \cdot \sqrt{\Delta t}$$

Now, we take the limit to continuous time, i.e., we increase the number of periods (n → ∞) while keeping the time horizon constant, i.e., Δt = T/n → 0.





$$S_{T} = S_{0} \prod_{i=0}^{n-1} e^{\Delta L_{(i+1)\Delta t}}$$

$$= S_{0} \exp\left\{\sum_{i=0}^{n-1} \left[\left(\mu - \frac{1}{2}\sigma^{2}\right)\Delta t + \sigma \cdot \nu_{(i+1)\Delta t} \cdot \sqrt{\Delta t}\right]\right\}$$

$$\approx S_{0} \exp\left\{\left(\mu - \frac{1}{2}\sigma^{2}\right)T + \sigma \cdot \sqrt{\Delta t} \cdot \sum_{i=1}^{n} \nu_{i\Delta t}\right\}$$

$$= S_{0} \exp\left\{\left(\mu - \frac{1}{2}\sigma^{2}\right)T + \sigma \cdot \sqrt{T} \cdot \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \nu_{i\Delta t}\right\}$$

According to the CLT:  $\frac{1}{\sqrt{n}} \sum_{i=1}^{n} \nu_{i\Delta t} \rightarrow_{d} Z_{T} \sim \mathcal{N}(0,1)$  as  $n \rightarrow \infty$ , i.e.,

$$S_T \rightarrow_d S_0 \exp\left\{\left(\mu - \frac{1}{2}\sigma^2\right)T + \sigma \cdot \sqrt{T} \cdot Z_T\right\}$$



• In the limit, the log return is normally distributed:

$$L_{T} = L_{0} + \left(\mu - \frac{1}{2}\sigma^{2}\right)T + \sigma \cdot \sqrt{T} \cdot Z_{T}$$

• Consequently, in the limit  $S_T$  is log-normally distributed with

mean: 
$$\mathbb{E}[S_T] = S_0 e^{\mu \cdot T}$$
  
variance:  $\operatorname{var}(S_T) = S_0^2 e^{2\mu \cdot T} [e^{\sigma^2 T} - 1]$ 

Does this mean that any discrete-time model converges to a log-normal distribution? No! But we need non-iid shok s.t. the CLT cannot be applied.
How can we model asset prices in continuous time?
AS<sub>t+st</sub> = S<sub>t</sub> [ p At + T 2<sub>t+st</sub> fat ]
Scotting for a S<sub>t</sub> = S<sub>t</sub> [ p At + T dW<sub>t</sub> ]

# Trading in Discrete Time

 $Y_{t} = \begin{pmatrix} n_{t} \\ S_{t} \end{pmatrix}$ 



- Assume that there is a frictionless financial market (i.e., no taxes, no transaction costs, no short-selling constraints, ...)
- Throughout the lecture we will be using vector notation:
  - *m* : number of basic assets
  - $Y_t$ : *m*-dimensional vector of asset prices at time *t*
- $\begin{aligned} \mathcal{Q}_{\ell} &= \begin{pmatrix} 2\\ \Lambda \end{pmatrix} \\ V_{\ell} &= 2M_{\ell} + \Lambda S_{L} \end{aligned}$  $\phi_t$  : vector of number of units of assets held at time t• Portfolio value generated by the *portfolio strategy* (or *trading* strategy)  $\phi$ : m

$$V_t = \phi'_t Y_t. = \sum_{i=1}^{1} \phi_{it} Y_{it}$$

• A portfolio strategy  $\phi$  is *self-financing* if trading neither generates nor destroys money, i.e., Trady does not dryp the partfilio

$$\phi_{t-\Delta t}'Y_t = \phi_t'Y_t.$$

# Trading in Discrete Time



• Suppose that rebalancing takes place at times  $0 < t_1 < \cdots < t_n = T$ , i.e.,  $t_i = j\Delta t$ .  $V_{+j+n} = \phi_{+j+n} Y_{+j+n} = \phi_{+j} Y_{+j+n}$  $V_T = V_0 + \sum^{n-1} (V_{t_{j+1}} - V_{t_j})$ (telescope rule)  $=V_0+\sum_{t_j}^{n-1}\phi_{t_j}'(Y_{t_{j+1}}-Y_{t_j})$  (self-financing portfolio) • The sum  $\sum_{j=0}^{n-1} \phi'_{t_j} \Delta Y_{t_{j+1}}$ .  $\sum_{\substack{n \to \infty \\ \Delta t \to 0}} V_0 + \int_0^T \phi'_t dY_t$ • The sum  $\sum_{j=0}^{n-1} \phi'_{t_j} \Delta Y_{t_{j+1}}$  converges in some sense to the stochastic integral  $\int_0^T \phi'_t dY_t$  even if the integrator is of infinite variation. • The continuous-time version of self-financing is  $V_T = V_0 + \int_0^T \phi'_t \, dY_t$ .

# From Discrete Time to Continuous Time



 We need adequate tools for modeling asset prices in continuous time that can be interpreted along the lines of

(1) 
$$\frac{\Delta B_{t+\Delta t}}{B_t} = r \cdot \Delta t$$
  
(2) 
$$\frac{\Delta S_{t+\Delta t}}{S_t} = \mu \cdot \Delta t + \sigma \cdot \nu_{t+\Delta t} \cdot \sqrt{\Delta t}$$

and that preserve the limit distribution of the stock return.Replace (1) by an ODE and (2) by an SDE:

$$(1') \quad \frac{dB_t}{B_t} = rdt$$
$$(2') \quad \frac{dS_t}{S_t} = \mu dt + \sigma dW_t$$

• Replace the self-financing condition  $\phi'_{t-\Delta t}Y_t = \phi'_tY_t$  by  $V_T = V_0 + \int_0^T \phi'_t \, dY_t$  for an adequately defined stochastic integral.



#### Discrete vs. Continuous Time Modeling

#### 2 Fundamentals from Stochastic Calculus

# Stochastic Processes



- Consider a filtered probability space  $(\Omega, \mathcal{A}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$ 
  - $\Omega$  denotes the state space.
  - $\mathcal{A} \subset 2^{\Omega}$  denotes a sigma algebra that contains all events for which probabilities can be assigned.
  - $(\mathcal{F}_t)_{t\geq 0}$  denotes the filtration, which models the set of information available at time t.
  - $\mathbb{P}:\mathcal{A}\to[0,1]$  is a probability measure, which we refer to as real-world probability measure.
- A stochastic process X is a collection of random variables (X<sub>t</sub>)<sub>t≥0</sub> indexed by time.

#### Remarks:

- Throughout the course, we assume that all processes are continuous (i.e., "no jumps" a.s.) and adapted (i.e., "realization  $X_t$  is known at time t"). Formulas become more involved if we relax this assumption.
- I will avoid technical terms (e.g., measurability, integrability), but focus on economic interpretations. I will rather assume that all processes satisfy all relevant conditions.



#### Definition (Brownian Motion)

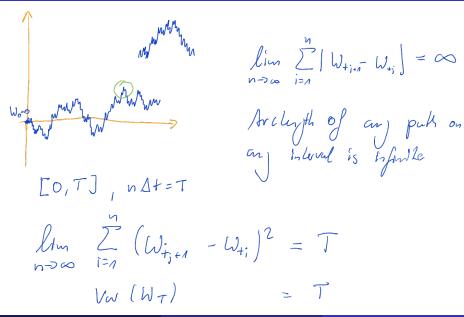
A one-dimensional (standard) Brownian motion (aka Wiener Process) is a stochastic process  $W = (W_t)_{t \ge 0}$  such that  $W_0 = 0$  a.s. and

- $W_t W_s \sim \mathcal{N}(0, t s)$  for  $0 \le s < t$  (stationary increments).
- W<sub>t</sub> − W<sub>s</sub> is independent of W<sub>u</sub> − W<sub>v</sub> for 0 ≤ v < u ≤ s < t (independent increments).</li>

- A *k*-dimensional standard Brownian motion  $W = (W_1, \dots, W_k)$  is a *k*-dimensional vector of independent Brownian motions.
- Notice that the paths of a Brownian motion are continuous (a.s.) but nowhere differentiable. In particular, the paths of Brownian motion have infinite length on any interval ("infinite variation").

# Brownian Motion







#### Definition (Martingale)

A stochastic process  $Z = (Z_t)_{t \ge 0}$  is said to be a *martingale* if "the best estimate of the future is the present", i.e.,

$$E_s[Z_t] = Z_s \qquad t \ge s$$

- Martingales relate to "fair games" and are often thought of as "purely stochastic" processes, that is, containing no trend or being constant in expectation..
- Example: Brownian motion is a martingale.
- There are many generalizations of martingales, e.g.,
  - Submartingales ("non-decreasing in expectation")
  - Supermartingales ("non-increasing in expectation")
  - Local martingales ("if stopped process is a martingale")
  - Semimartingales ("local martingale + process of finite variation")

# Itô Integral



• The stochastic integral (a.k.a. Itô integral) is defined by

$$\int_0^T X_t \, \mathrm{d}Z_t = \lim_{n \to \infty} \sum_{j=0}^n X_{t_j} (Z_{t_{j+1}} - Z_{t_j})$$

- where Z is a semimartingale, X is an adapted process, and the stochastic limit is taken in the sense of refining partitions (i.e., intermediate points  $t_0, t_1, \ldots, t_n$  become more and more dense on the interval [0, T] as *n* tends to infinity).
- The construction of the limit and prove of convergence is not trivial, since in general the integrator is of infinite variation.
- Such a limit does not necessarily exist pathwise.
- Note: by contrast to the Riemann-Stieltjes integral, the integrand is evaluated at the left end  $t_i$ .
- The stochastic integral is itself a random variable.



### Definition (Stochastic Differential Equation)

Let W be a standard Brownian motion. An expression of the form

$$dX_t = \mu(t, X_t) dt + \sigma(t, X_t) dW_t$$

 $dX = X_{\pm} - X_{0}$ 

for given functions  $\mu(t, X_t)$  (drift) and  $\sigma(t, X_t)$  (volatility) is called a stochastic differential equation (SDE) driven by Brownian motion and should be understood as a short-hand notation for the integral equation

$$X_t = X_0 + \int_0^t \mu(s, X_s) \,\mathrm{d}s + \int_0^t \sigma(s, X_s) \,\mathrm{d}W_s.$$

- If the drift  $\mu(t, X_t)$  is zero, then the solution is a martingale.
- This definition can be generalized to SDEs driven by jump processes (e.g., Poisson processes).

# Quadratic (Co-)Variation



• Let X, Y be two real-valued stochastic processes, then their *quadratic covariation process* is defined as

$$[X, Y]_t = \lim_{\Delta t \to 0} \sum_{j=0}^t (X_{t_{j+1}} - X_j)(Y_{t_{j+1}} - Y_j)$$

- The quadratic variation process of X is defined by
- $\begin{bmatrix} \alpha \gamma_{1} b \chi \end{bmatrix}_{z = \alpha \cdot b \cdot [\chi, \gamma]} [X]_{t} = [X, X]_{t}$ 
  - Rules for quadratic (co)-variation:
    - linearity in both arguments
    - [X,g] = 0 if g is a continuous function of bounded variation
    - d[W<sub>1</sub>, W<sub>2</sub>] = ρ dt for BMs with correlation coefficient ρ; d[W] = dt
    - if  $dX = \mu_X dt + \sigma_X dW_1$  and  $dY = \mu_Y dt + \sigma_Y dW_2$ , then

$$d[X, Y] = \sigma_X \sigma_Y \rho \, dt, \qquad d[X] = \sigma_X^2 \, dt$$



#### Theorem (Itô's Lemma for continuous semimartingales)

Let X be a continuous real-valued semimartingale, and  $f: \mathbb{R}^+ \times \mathbb{R} \to \mathbb{R}$  is a  $C^{1,2}$ -function, then

$$df(t,X_t) = \frac{\partial}{\partial t}f(t,X_t) dt + \frac{\partial}{\partial x}f(t,X_t) dX_t + \frac{1}{2}\frac{\partial^2}{\partial x^2}f(t,X_t) d[X,X]_t.$$

#### Theorem (Itô's Lemma for Itô processes)

Let X be an Itô process  $dX_t = \mu_X dt + \sigma_X dW_t$ , and  $f : \mathbb{R}^+ \times \mathbb{R} \to \mathbb{R}$  is a  $C^{1,2}$ -function, then

$$df(t, X_t) = \left[\frac{\partial}{\partial t}f(t, X_t) + \frac{\partial}{\partial x}f(t, X_t)\mu_X + \frac{1}{2}\frac{\partial^2}{\partial x^2}f(t, X_t)\sigma_X^2\right]dt + \frac{\partial}{\partial x}f(t, X_t)\sigma dW_t.$$

1tô-tem



**Problem:** Derive the stock price in the Black-Scholes model and show that it is strictly positive almost surely.

Solution: 
$$dS_{t} = S_{t}(mdt + \forall dW_{t})$$

$$f(+, x) = \log(x)$$

$$f_{t} = 0, \quad f_{x} = \frac{1}{x}, \quad f_{xx} = -\frac{1}{x}$$

$$d\log S_{t} = f_{t}dt + f_{x}dx_{t} + \frac{1}{2}f_{xx}dEXJ_{t}$$

$$= \frac{1}{S_{t}}S_{t}(mdt + \forall dW_{t}) + \frac{1}{2}(-\frac{1}{S^{t}})S^{t}\nabla^{2}dt$$

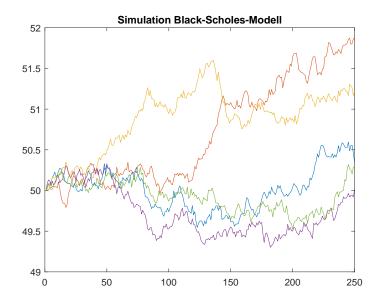
$$= (M - \frac{1}{2}\nabla^{2})dt + \forall dW$$



=> 
$$log St = log So + (n - \frac{1}{2}\sigma^2)t + \sigma Wt$$
  
 $St = So exp \left\{ (n - \frac{2}{2}\sigma^2)t + \sigma Wt \right\}$ 
Brownson  
Brownson  
Holdon  
=> Slo2 proce remains shirely posothire of  
 $S_0 > 0.$ 

# Geometric Brownian Motion







#### Theorem (Itô's Lemma for continuous semimartingales)

Let  $X = (X_t^1, \ldots, X_t^n)_{t \ge 0}$  be a continuous  $\mathbb{R}^n$ -valued semimartingale, and  $f : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}$  is a  $C^{1,2}$ -function, then

$$df(t, X_t) = \frac{\partial}{\partial t} f(t, X_t) dt + \sum_{i=1}^n \frac{\partial}{\partial x_i} f(t, X_t) dX_t^i$$
$$+ \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial x_i \partial x_j} f(t, X_t) d[X^i, X^j]_t.$$

Special Case: f(X, Y) = XY: Itô product rule:

$$d(XY)_t = X_t dY_t + Y_t dX_t + d[X, Y]_t$$



#### Theorem (Itô's Lemma for multivariate Itô processes)

Let W be a k-dimensional standard Brownian motion, X be a  $\mathbb{R}^n$ -valued Itô process with dynamics

$$\mathrm{d}X_t = \mu_X \mathrm{d}t + \sigma_X \mathrm{d}W_t$$

for sufficiently smooth functions  $\mu_X : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}^n$  and  $\sigma_X : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}^{n \times k}$ . Let  $f : \mathbb{R}^+ \times \mathbb{R}^n \to \mathbb{R}$  is a  $C^{1,2}$ -function with gradient  $\nabla f(t, X_t)$  and Hessian matrix  $H_f(t, X_t)$ , then

$$df(t, X_t) = \left[\underbrace{\frac{\partial}{\partial t} f(t, X_t)}_{\in \mathbb{R}^n} + \underbrace{\nabla f(t, X_t)}_{\in \mathbb{R}^n} \cdot \underbrace{\mu_X}_{\in \mathbb{R}^n} + \frac{1}{2} tr\left(\underbrace{H_f(t, X_t)}_{\in \mathbb{R}^{n \times n}} \underbrace{\sigma_X}_{\in \mathbb{R}^{n \times k}} \underbrace{\sigma_X'}_{\in \mathbb{R}^{k \times n}}\right)\right] dt$$
$$+ \underbrace{\nabla f(t, X_t)}_{\in \mathbb{R}^n} \underbrace{\sigma_X}_{\in \mathbb{R}^{n \times k}} \underbrace{dW_t}_{\in \mathbb{R}^k}$$

# Example: Relative Asset Prices



$$dS_{t} = S_{t}\left[p dt + \sigma dW_{t}\right] , dB_{t} = B_{t} r dt$$

$$(!) What are the dynamics of  $\frac{S}{0}$ ?  $f(x,g) = \frac{x}{y}, fx = \frac{1}{y}, fy = -\frac{x}{y^{2}}$ 

$$d(\frac{S}{0}) = \frac{1}{B} dS - \frac{S}{B^{2}} dB \qquad fxx = 0, fyy = 2\frac{x}{y^{3}}$$

$$= \frac{1}{B} S\left(p dt + \sigma dW\right) - \frac{S}{B^{2}} Br dt \qquad fxy = -\frac{1}{y^{2}}$$

$$= \frac{S}{B}\left[\left(p - r + 1dt + \sigma dW\right)\right] \stackrel{\text{d}}{=} \frac{S}{B}\left((p - r)dt + \sigma dW - \sigma \lambda dt\right)$$

$$Construct a measure Q \sim P \quad s.t. \quad \frac{S}{0} \quad is a Q - markgule:$$

$$Und_{t} Q : drift much le 2ro$$

$$dW = \lambda dt + dW c \Rightarrow dW = dW - \lambda dt$$$$



#### Definition (Equivalent Probability Measure)

Two probability measures  $\mathbb{P}$  and  $\mathbb{Q}$  are said to be *equivalent*,  $\mathbb{P} \sim \mathbb{Q}$ , if both measures possess the same null sets, i.e., for all events  $A \in \mathcal{A}$ 

 $\mathbb{P}(A) = 0 \iff \mathbb{Q}(A) = 0.$ 

- In our pricing applications, we consider equivalent probability measures that are associated to a numéraire.
- A numéraire is any self-financing portfolio  $\phi$  that generates strictly positive wealth  $V_t^{\phi} = \phi'_t Y_t$
- A probability measure Q ~ P is said to be an equivalent martingale measure if for every asset with price process Y<sup>i</sup> (i = 1,...,m) the price expressed in terms of the numéraire V<sup>φ</sup><sub>t</sub> is a martingale under Q.

# Change of Measure - Radon-Nikodym Theorem



 The following theorem states how to switch between two equivalent probability measures.

#### Theorem (Radon-Nikodym)

Let  $\mathbb{P} \sim \mathbb{Q}$  denote two equivalent probability measures, then there exists a unique (a.s.), positive random variable  $\theta = \frac{d\mathbb{Q}}{d\mathbb{P}}$  such that

$$\mathbb{E}^{\mathbb{Q}}[X] = \mathbb{E}^{\mathbb{P}}[ heta X], \qquad \mathbb{E}^{\mathbb{P}}[X] = \mathbb{E}^{\mathbb{Q}}\Big[rac{X}{ heta}\Big]$$

for all real-valued random variables X. In particular,

$$\mathbb{Q}[A] = \mathbb{E}^{\mathbb{P}}[\theta \, 1_A]$$

 $\theta$  is called the *Radon-Nikodym density* (or *Radon-Nikodym derivative*).

• Critical Question: How can we perform a change of measure if the market is driven by Brownian motions?

Christoph Hambel (TiSEM)



#### Theorem (Girsanov)

Suppose that a measure  $\mathbb Q$  is defined in terms of a measure  $\mathbb P$  by the Radon-Nikodym process  $(\theta_t)_{t\geq 0},$  with

$$\mathrm{d}\theta_t = -\lambda_t \theta_t \,\mathrm{d}W_t$$

where W is a Brownian motion under  $\mathbb{P}$  and  $\lambda$  is a continuous adapted process. Then the process  $\widetilde{W}$  defined by  $\widetilde{W}_0 = 0$  and

$$\mathrm{d}\,\widetilde{W}_t = \lambda_t\,\mathrm{d}\,t + \mathrm{d}\,W_t$$

is a Brownian motion under  $\mathbb{Q}$ .

This works as well for vector BMs; in this case, write

$$\mathrm{d}\theta_t = -\theta_t \lambda_t' \,\mathrm{d}W_t, \quad \mathrm{d}\widetilde{W}_t = \lambda_t \,\mathrm{d}t + \mathrm{d}W_t.$$

# Some Remarks



The stochastic differential equation dθ<sub>t</sub> = -λ<sub>t</sub>θ<sub>t</sub> dW<sub>t</sub> has a unique solution, the Radon-Nikodym process:

$$heta_t = \mathcal{E}(\lambda)_t = \exp\left(-\int_0^t \lambda_s \mathrm{d} W_s - rac{1}{2}\int_0^t \lambda_s^2 \mathrm{d} s
ight)$$

- The process *E*(λ) is called the stochastic exponential or Doléans-Dade exponential of λ.
- The Radon-Nikodym *derivative* is given by

$$\theta_{T} = \exp\left(-\int_{0}^{T} \lambda_{s} \mathrm{d}W_{s} - \frac{1}{2}\int_{0}^{T} \lambda_{s}^{2} \mathrm{d}s\right)$$

• The Radon-Nikodym *process* is a P-martingale, i.e.,

$$\theta_t = \mathbb{E}_t[\theta_T].$$