



Interest Rate Models: from Parametric Statistics to Infinite Dimensional Stochastic Analysis

René Carmona

Bendheim Center for Finance ORFE & PACM, Princeton University email: rcarmna@princeton.edu URL: http://www.princeton.edu/ rcarmona/

IPAM / Financial Math January 3-5, 2001



Chapter 6













Solution of the SDE





Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$





Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$

 $\bullet a \in \mathbb{R} \text{ or } a > 0, b > 0$





Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$

- $\bullet a \in \mathbb{R} \text{ or } a > 0, b > 0$
- $\{w_t\}_{t\geq 0}$ one dimensional Wiener process





Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$

3/17

K

Ν

- $a \in \mathbb{R}$ or a > 0, b > 0
- $\{w_t\}_{t\geq 0}$ one dimensional Wiener process
- ξ_0 (implicitly) assumed to be independent of $\{w_t\}_{t\geq 0}$

Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$

3/17

K

N

- $a \in \mathbb{R}$ or a > 0, b > 0
- $\{w_t\}_{t\geq 0}$ one dimensional Wiener process
- ξ_0 (implicitly) assumed to be independent of $\{w_t\}_{t\geq 0}$
- Explicit solution

Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$

- $a \in \mathbb{R}$ or a > 0, b > 0
- $\{w_t\}_{t\geq 0}$ one dimensional Wiener process
- ξ_0 (implicitly) assumed to be independent of $\{w_t\}_{t\geq 0}$
- Explicit solution

$$\xi_t = e^{-ta}\xi_0 + \sqrt{b} \int_0^t e^{-(t-s)a} dw_s, \qquad 0 \le t < +\infty$$





Solution of the SDE

$$d\xi_t = -a\xi_t dt + \sqrt{b}dw_t$$

- $a \in \mathbb{R}$ or a > 0, b > 0
- $\{w_t\}_{t\geq 0}$ one dimensional Wiener process
- ξ_0 (implicitly) assumed to be independent of $\{w_t\}_{t\geq 0}$
- Explicit solution

$$\xi_t = e^{-ta}\xi_0 + \sqrt{b} \int_0^t e^{-(t-s)a} dw_s, \qquad 0 \le t < +\infty$$















$$\mathbb{E}\xi_t = e^{-ta}\mathbb{E}\xi_0$$

• Autocovariance function





$$\mathbb{E}\xi_t = e^{-ta}\mathbb{E}\xi_0$$

• Autocovariance function

$$\operatorname{cov}\{\xi_s,\xi_t\} = [\operatorname{var}\{\xi_0\} + \frac{b}{2a}(e^{2(s\wedge t)a} - 1)]e^{-(s+t)a}$$





$$\mathbb{E}\xi_t = e^{-ta}\mathbb{E}\xi_0$$

Autocovariance function

$$\operatorname{cov}\{\xi_s,\xi_t\} = [\operatorname{var}\{\xi_0\} + \frac{b}{2a}(e^{2(s\wedge t)a} - 1)]e^{-(s+t)a}$$

• $\{\xi_t\}$ is a Gaussian process whenever ξ_0 is Gaussian

$$\mathbb{E}\xi_t = e^{-ta}\mathbb{E}\xi_0$$

Autocovariance function

$$\operatorname{cov}\{\xi_s,\xi_t\} = [\operatorname{var}\{\xi_0\} + \frac{b}{2a}(e^{2(s\wedge t)a} - 1)]e^{-(s+t)a}$$

- $\{\xi_t\}$ is a Gaussian process whenever ξ_0 is Gaussian
- $\{\xi_t\}$ is a (strong) Markov process.
- $\{\xi_t\}$ has a unique invariant measure N(0, b/2a)

$$\mathbb{E}\xi_t = e^{-ta}\mathbb{E}\xi_0$$

Autocovariance function

$$\operatorname{cov}\{\xi_s,\xi_t\} = [\operatorname{var}\{\xi_0\} + \frac{b}{2a}(e^{2(s\wedge t)a} - 1)]e^{-(s+t)a}$$

- $\{\xi_t\}$ is a Gaussian process whenever ξ_0 is Gaussian
- $\{\xi_t\}$ is a (strong) Markov process.
- $\{\xi_t\}$ has a unique invariant measure N(0, b/2a)
- if $\xi_0 \sim N(0, b/2a)$, $\{\xi_t\}$ is stationary ergodic Markov (mean zero) Gaussian process. Autocovariance function:

$$\mathbb{E}\xi_s\xi_t = \frac{b}{2a}e^{-a|t-s|}$$















a > 0

 \longrightarrow A $n \times n$ symmetric positive definite matrix





5/17

$\begin{array}{cccc} a > 0 & \longrightarrow & A & n \times n \text{ symm} \\ b > 0 & \longrightarrow & B & n \times n \text{ symm} \end{array}$

 \longrightarrow A $n \times n$ symmetric positive definite matrix \longrightarrow B $n \times n$ symmetric positive definite matrix





5/17

 $\begin{array}{c} a > 0 \\ b > 0 \\ \{w_t\}_{t \ge 0} 1 - \text{dim. Wiener Proc.} \end{array} \longrightarrow$

 $\begin{array}{rcl} &\longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ &\longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ &\longrightarrow & \{W_t\}_{t \geq 0} & n - \text{dim. Wiener Proc.} \end{array}$





5/17

 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & \{W_t\}_{t \geq 0} & n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE





 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & & \{W_t\}_{t \geq 0} n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE

 $dX_t = -AX_t dt + \sqrt{B} dW_t$







 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & \{W_t\}_{t \geq 0} & n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE

$$dX_t = -AX_t dt + \sqrt{B} dW_t$$

• $\{W_t\}_{t\geq 0}$ *n*-dimensional Wiener process







 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & & \{W_t\}_{t \geq 0} n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE

$$dX_t = -AX_t dt + \sqrt{B} dW_t$$

- $\{W_t\}_{t\geq 0}$ *n*-dimensional Wiener process
- X_0 (implicitly) assumed to be independent of $\{W_t\}_{t\geq 0}$







 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & & \{W_t\}_{t \geq 0} n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE

$$dX_t = -AX_t dt + \sqrt{B} dW_t$$

- $\{W_t\}_{t\geq 0}$ *n*-dimensional Wiener process
- X_0 (implicitly) assumed to be independent of $\{W_t\}_{t\geq 0}$
- Explicit solution



 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & & \{W_t\}_{t \geq 0} n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE

$$dX_t = -AX_t dt + \sqrt{B} dW_t$$

- $\{W_t\}_{t\geq 0}$ *n*-dimensional Wiener process
- X_0 (implicitly) assumed to be independent of $\{W_t\}_{t\geq 0}$
- Explicit solution

$$X_{t} = e^{-tA}X_{0} + \int_{0}^{t} e^{-(t-s)A}\sqrt{B}dW_{s},$$

 $0 \le t < +\infty$



 $\begin{array}{rcl} & \longrightarrow & A & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & B & n \times n \text{ symmetric positive definite matrix} \\ & \longrightarrow & & \{W_t\}_{t \geq 0} n - \text{dim. Wiener Proc.} \end{array}$

As before, solution of the SDE

$$dX_t = -AX_t dt + \sqrt{B} dW_t$$

- $\{W_t\}_{t\geq 0}$ *n*-dimensional Wiener process
- X_0 (implicitly) assumed to be independent of $\{W_t\}_{t\geq 0}$
- Explicit solution

$$X_{t} = e^{-tA}X_{0} + \int_{0}^{t} e^{-(t-s)A}\sqrt{B}dW_{s},$$

 $0 \le t < +\infty$



6/17



K







$$\mathbb{E}X_t = e^{-tA}\mathbb{E}X_0$$

• Autocovariance function



K

M

$$\mathbb{E}X_t = e^{-tA}\mathbb{E}X_0$$

• Autocovariance function

$$\operatorname{cov}\{X_s, X_t\} = e^{-sA} \operatorname{var}\{X_0\} e^{-tA} + \int_0^{s \wedge t} e^{-(s-u)A} B e^{-(t-u)A} du$$

$$\mathbb{E}X_t = e^{-tA} \mathbb{E}X_0$$

Autocovariance function

$$\operatorname{cov}\{X_s, X_t\} = e^{-sA} \operatorname{var}\{X_0\} e^{-tA} + \int_0^{s \wedge t} e^{-(s-u)A} B e^{-(t-u)A} du$$

• $\{X_t\}$ is a Gaussian process whenever X_0 is Gaussian

$$\mathbb{E}X_t = e^{-tA}\mathbb{E}X_0$$

Autocovariance function

$$\operatorname{cov}\{X_s, X_t\} = e^{-sA} \operatorname{var}\{X_0\} e^{-tA} + \int_0^{s \wedge t} e^{-(s-u)A} B e^{-(t-u)A} du$$

- $\{X_t\}$ is a Gaussian process whenever X_0 is Gaussian
- $\{X_t\}$ is a (vector valued) Markov process.
- Could drive the system with a *r*-dimensional Wiener process:
 - The $n \times n$ matrix \sqrt{B} replaced by a $d \times r$ matrix C



$$\mathbb{E}X_t = e^{-tA}\mathbb{E}X_0$$

Autocovariance function

$$\operatorname{cov}\{X_s, X_t\} = e^{-sA} \operatorname{var}\{X_0\} e^{-tA} + \int_0^{s \wedge t} e^{-(s-u)A} B e^{-(t-u)A} du$$

- $\{X_t\}$ is a Gaussian process whenever X_0 is Gaussian
- $\{X_t\}$ is a (vector valued) Markov process.
- Could drive the system with a *r*-dimensional Wiener process:
 - The $n \times n$ matrix \sqrt{B} replaced by a $d \times r$ matrix C
 - role of B played by C^*C



$$\mathbb{E}X_t = e^{-tA}\mathbb{E}X_0$$

Autocovariance function

$$\operatorname{cov}\{X_s, X_t\} = e^{-sA} \operatorname{var}\{X_0\} e^{-tA} + \int_0^{s \wedge t} e^{-(s-u)A} B e^{-(t-u)A} du$$

- $\{X_t\}$ is a Gaussian process whenever X_0 is Gaussian
- $\{X_t\}$ is a (vector valued) Markov process.
- Could drive the system with a *r*-dimensional Wiener process:
 - The $n \times n$ matrix \sqrt{B} replaced by a $d \times r$ matrix C
 - role of B played by C^*C







• $\{X_t\}$ has a unique invariant measure, say $\mu = N(0, \Sigma)$ *n*-dimensional Gaussian measure

$$\mu(dx) = \frac{1}{Z(\Sigma)} e^{-\langle \Sigma^{-1}x, x \rangle/2} dx,$$

 $Z(\Sigma)$ being a normalizing constant

$$\Sigma = \int_0^\infty e^{-sA} B e^{-sA} \, ds.$$

Notice that the fact that Σ solves:

$$\Sigma A + A\Sigma = B$$

is the crucial property of the matrix $\boldsymbol{\Sigma}$



8/17

• If $X_0 \sim \mu$, $\{X_t\}_{t\geq 0}$ is stationary mean zero (Markov) Gaussian process with autocovariance tensor:

$$\Gamma(s,t) = \mathbb{E}_{\mu}\{X_s X_t\} = \begin{cases} \Sigma e^{-(t-s)A} & \text{whenever} \quad 0 \le s \le t \\ e^{-(s-t)A}\Sigma & \text{whenever} \quad 0 \le t \le s. \end{cases}$$



• If $X_0 \sim \mu$, $\{X_t\}_{t \ge 0}$ is stationary mean zero (Markov) Gaussian process with autocovariance tensor:

$$\Gamma(s,t) = \mathbb{E}_{\mu}\{X_s X_t\} = \begin{cases} \Sigma e^{-(t-s)A} & \text{whenever} \quad 0 \le s \le t \\ e^{-(s-t)A}\Sigma & \text{whenever} \quad 0 \le t \le s. \end{cases}$$

• Cumbersome formulae when A & B do not commute





• If $X_0 \sim \mu$, $\{X_t\}_{t \ge 0}$ is stationary mean zero (Markov) Gaussian process with autocovariance tensor:

$$\Gamma(s,t) = \mathbb{E}_{\mu}\{X_s X_t\} = \begin{cases} \Sigma e^{-(t-s)A} & \text{whenever} \quad 0 \le s \le t \\ e^{-(s-t)A}\Sigma & \text{whenever} \quad 0 \le t \le s. \end{cases}$$

• Cumbersome formulae when A & B do not commute





• If A & B do commute





• If A & B do commute

$$\Sigma = B \int_0^\infty e^{-2sA} \, ds = B(2A)^{-1}$$



$$\Sigma = B \int_0^\infty e^{-2sA} \, ds = B(2A)^{-1}$$

• If $x, y \in \mathbb{R}^n$ we have:

$$< x, \Gamma(s,t)y >= \mathbb{E}_{\mu} \{ < x, X_s > < y, X_t > \}$$
$$= <\sqrt{\Sigma}x, \sqrt{\Sigma}e^{-|t-s|A}y >$$
$$= < x, e^{-|t-s|A}y >_{\Sigma}$$

with the notation:

$$< \cdot, \cdot >_D = <\sqrt{D} \cdot, \sqrt{D} \cdot > =$$







$$\Sigma = B \int_0^\infty e^{-2sA} \, ds = B(2A)^{-1}$$

• If $x, y \in \mathbb{R}^n$ we have:

$$< x, \Gamma(s,t)y >= \mathbb{E}_{\mu} \{ < x, X_s > < y, X_t > \}$$
$$= <\sqrt{\Sigma}x, \sqrt{\Sigma}e^{-|t-s|A}y >$$
$$= < x, e^{-|t-s|A}y >_{\Sigma}$$

with the notation:

$$< \cdot, \cdot >_D = <\sqrt{D} \cdot, \sqrt{D} \cdot > =$$





• The Markov process $\{X_t\}_{t\geq 0}$ is symmetric (Fukushima)



- The Markov process $\{X_t\}_{t\geq 0}$ is symmetric (Fukushima)
- Generated by the Dirichlet form of the measure μ, i.e. to the quadratic form:

$$Q(f,g) = \int_{\mathbb{R}^n} < \nabla f(x), \overline{\nabla g(x)} >_B \mu_{\Sigma}(dx)$$

defined on the subspace \mathcal{Q} of $L^2(\mathbb{R}^n, \mu_{\Sigma}(dx))$ comprising the absolutely continuous functions whose first derivatives (in the sense of distributions) are still in the space $L^2(\mathbb{R}^n, \mu_{\Sigma}(dx))$.





Generalizations of the Three Approaches used in the Finite Dimensional Case





Generalizations of the Three Approaches used in the Finite Dimensional Case 11/17

K

M

• The state space \mathbb{R}^d of the Wiener noise is replaced by a (possibly infinite dimensional) Hilbert space, say *H*, or a Banach space *E*

Generalizations of the Three Approaches used in the Finite Dimensional Case

11/17

K

Ν

- The state space \mathbb{R}^d of the Wiener noise is replaced by a (possibly infinite dimensional) Hilbert space, say *H*, or a Banach space *E*
- The Wiener noise terms $\xi_t^{(j)}$ are replaced by a Wiener process in H or E

Generalizations of the Three Approaches used in the Finite Dimensional Case

- The state space R^d of the Wiener noise is replaced by a (possibly infinite dimensional) Hilbert space, say H, or a Banach space E
- The Wiener noise terms $\xi_t^{(j)}$ are replaced by a Wiener process in H or E
- The $d \times n$ dispersion matrix B is replaced by a map σ from H or E into the state space F of f_t replacing \mathbb{R}^n
- The $n \times n$ drift coefficient matrix A is replaced by a (possibly unbounded) operator which we will still denote by A



Generalizations of the Three Approaches used in the Finite Dimensional Case

- The state space R^d of the Wiener noise is replaced by a (possibly infinite dimensional) Hilbert space, say H, or a Banach space E
- The Wiener noise terms $\xi_t^{(j)}$ are replaced by a Wiener process in H or E
- The $d \times n$ dispersion matrix B is replaced by a map σ from H or E into the state space F of f_t replacing \mathbb{R}^n
- The $n \times n$ drift coefficient matrix A is replaced by a (possibly unbounded) operator which we will still denote by A



• The role played by $\sqrt{B}dW_t$ is now played by a *H*-valued (cylindrical) Wiener process with covariance given by the operator *B*. The appropriate mathematical object is a linear function, say W_B , from the tensor product $L^2([0,\infty), dt) \hat{\otimes}_2 H_B$ into a Gaussian subspace of $L^2(\Omega, \mathcal{F}, \mathbb{P})$ where $(\Omega, \mathcal{F}, \mathbb{P})$ is the complete probability space we work with. If $x \in H_B$ and $t \geq 0$, then $W_B(\mathbf{1}_{[0,t)}(\cdot)x)$ should play the same role as $< x, W_t >$ in the finite dimensional case.







13/17

For the sake of the present discussion:





For the sake of the present discussion:

• Take $\alpha_t \equiv 0$





For the sake of the present discussion:

- Take $\alpha_t \equiv 0$
- Choose $\sigma_t \equiv \sigma$ deterministic & independent of t

$$\frac{df_t}{dt} = -Af_t + \sigma \frac{dW}{dt}$$

• SPDE when A is a partial differential operator





For the sake of the present discussion:

- Take $\alpha_t \equiv 0$
- Choose $\sigma_t \equiv \sigma$ deterministic & independent of t

$$\frac{df_t}{dt} = -Af_t + \sigma \frac{dW}{dt}$$

- SPDE when A is a partial differential operator
- Integral form

$$f_t = f_0 - \int_0^t A f_s ds + \sigma W(t)$$





• Weak Form: for $f^* \in H^*$

$$< f^*, f_t > = < f^*, f_0 > - \int_0^t < A^* f^*, f_s > ds + < \sigma^* f^*, W(t) > 0$$

which makes sense when f^* belongs to the domain $\mathcal{D}(A^*)$ of the adjoint operator A^* and the domain $\mathcal{D}(\sigma^*)$ of the adjoint operator σ^* . Very seldom tractable

• Evolution Form (variation of constant formula):

$$f_t = e^{tA} f_0 + \int_0^t e^{(t-s)S} \sigma dW(s)$$

This requires that the exponentials of operators exist, i.e. that *A* generates a semigroup of operators.







15/17



K

◀

M

• $X = \{X_t; t \ge 0\}$ stochastic process in a Banach/Hilbert space F





- $X = \{X_t; t \ge 0\}$ stochastic process in a Banach/Hilbert space F
- \bullet Probability space $(\Omega, \mathcal{F}, \mathbb{P})$





• $X = \{X_t; t \ge 0\}$ stochastic process in a Banach/Hilbert space F

15/17

K

N

- \bullet Probability space $(\Omega, \mathcal{F}, \mathbb{P})$
- Filtration $(\mathcal{F}_t)_{t\geq 0}$ (satisfying the usual assumptions)

- $X = \{X_t; t \ge 0\}$ stochastic process in a Banach/Hilbert space F
- Probability space $(\Omega, \mathcal{F}, \mathbb{P})$
- Filtration $(\mathcal{F}_t)_{t\geq 0}$ (satisfying the usual assumptions)
- Drift operator A, possibly unbounded operator on F.
 - A is the infinitesimal generator of a C_0 -semigroup $\{e^{tA}; t \ge 0\}$ of bounded operators on F.
 - The domain of \boldsymbol{A} ,

$$\mathcal{D}(A) = \{ f \in F; \lim_{t \to 0} \frac{e^{tA}f - f}{t} \text{ exists.} \},\$$

is (generally) is a proper subset of F



K

N

- $X = \{X_t; t \ge 0\}$ stochastic process in a Banach/Hilbert space F
- Probability space $(\Omega, \mathcal{F}, \mathbb{P})$
- Filtration $(\mathcal{F}_t)_{t\geq 0}$ (satisfying the usual assumptions)
- Drift operator A, possibly unbounded operator on F.
 - A is the infinitesimal generator of a C_0 -semigroup $\{e^{tA}; t \ge 0\}$ of bounded operators on F.
 - The domain of \boldsymbol{A} ,

$$\mathcal{D}(A) = \{ f \in F; \lim_{t \to 0} \frac{e^{tA}f - f}{t} \text{ exists.} \},\$$

is (generally) is a proper subset of F



K

N

Noise W = {W_t; t ≥ 0} is a Wiener process in a real separable Banach space E with H_W the reproducing kernel Hilbert space associated with the Guassian measure μ (abstract Wiener space)

$$E^* \hookrightarrow H^*_W$$

$$\uparrow \quad (\text{Riesz identification})$$

$$H_W \hookrightarrow E$$

Noise W = {W_t; t ≥ 0} is a Wiener process in a real separable Banach space E with H_W the reproducing kernel Hilbert space associated with the Guassian measure μ (abstract Wiener space)

 $\begin{array}{rccc} E^* \hookrightarrow & H^*_W \\ & \uparrow & (\mbox{ Riesz identification}) \\ & H_W & \hookrightarrow E \end{array}$

• The variance/covariance operator $B : E \to F$ is a bounded linear operator (thus it has a restriction to H_W and this restriction is Hilbert-Schmidt when *F* is a Hilbert space.)

Note one could take *B* from H_W only if we start with a cylindrical Brownian motion.

Formally the Ornstein Uhlenbeck process satisfies the stochas-

tic differential equation

$$dX_t = AX_t dt + BdW_t$$

or in integral form

$$X_t = X_0 + \int_0^t AX_s ds + \int_0^t BdW_s.$$



