

# Applications of large deviations in finance and mathematical physics.

Martin Forde

DCU, Dept of Mathematics

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- ▶ Motivation and definition of the large deviation principle (LDP).
- ▶ Examples - Brownian motion, Cramér's theorem, Lévy processes, Sanov's theorem.
- ▶ The Brownian sheet.
- ▶ Saddlepoint methods; the Feynman path integral.
- ▶ The Donsker-Varadhan LDP for the occupation measure of the Ornstein Uhlenbeck process  $dY_t = -\theta Y_t dt + dW_t$  for  $\theta > 0$ .
- ▶ Applications to stochastic volatility models - the Ornstein-Uhlenbeck and CEV-Heston models.
- ▶ Large deviations for the maximum likelihood estimator of  $\theta$ .
- ▶ Application to SPDEs - Freidlin-Wentzell theory for the stochastic heat equation.

# The Large deviation principle (LDP): motivation

- Suppose we have sequence of random variables  $(X_n)$  such that  $X_n$  is concentrated around  $x_0$  as  $n \rightarrow \infty$ , and for sets  $A$  away from  $x_0$ ,  $\mathbb{P}(X_n \in A)$  tends to zero exponentially rapidly in  $n$ :

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(X_n \in A) = -I(A)$$

$$\text{i.e. } \forall \delta > 0, \quad e^{-n(I(A)+\delta)} \leq \mathbb{P}(X_n \in A) \leq e^{-n(I(A)-\delta)}$$

for  $n = n(\delta)$  sufficiently large, and some *rate function*  $I \geq 0$ .

- Example:** for standard Brownian motion  $(W_t)$ ,  $W_t \rightarrow 0$  a.s. as  $t \rightarrow 0$  and (by SLLN)  $\frac{W_t}{t} \rightarrow 0$  a.s. as  $t \rightarrow \infty$ , but

$$\begin{aligned} \lim_{t \rightarrow 0} t \log \mathbb{P}(W_t > x) &= -\frac{1}{2}x^2, \\ \lim_{t \rightarrow \infty} \frac{1}{t} \log \mathbb{P}\left(\frac{W_t}{t} > x\right) &= -\frac{1}{2}x^2 \end{aligned}$$

for  $x > 0$ .

# The Large deviation principle (LDP): definition

**Definition.** A sequence of random variables  $(X_n)$  in a topological space  $S$  satisfies the LDP with non-negative lower semicontinuous rate function  $I$  if we have the following exponential upper/lower bounds for  $A \in \mathcal{B}(S)$ :

$$\begin{aligned} -\inf_{x \in A^\circ} I(x) &\leq \liminf_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(X_n \in A) \\ &\leq \limsup_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(X_n \in A) \leq -\inf_{x \in \bar{A}} I(x). \end{aligned}$$

**Definition.**  $X_n$  is said to satisfy the weak LDP if

$$\lim_{\delta \rightarrow 0} \lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(X_n \in B_\delta) = -I(x).$$

- ▶ **Cramér's theorem.** Let  $(X_i)$  be an i.i.d. sequence of random variables with finite mean  $\mathbb{E}(X_1) < \infty$  and cumulant generating function

$$V(p) = \log \mathbb{E}(e^{pX_1}).$$

Then  $\bar{S}_n = \frac{1}{n} \sum_{i=1}^n X_i$  satisfies the LDP with rate function equal to the *Fenchel-Legendre transform*  $V^*(x) = \sup_{p \in \mathbb{R}} \{px - V(p)\}$ . For Brownian motion,  $V(p) = \frac{1}{2}p^2$ ,  $V^*(x) = \frac{1}{2}x^2$ .

- ▶ A **Lévy process**  $(X_t)$  has i.i.d. increments, so  $(\frac{X_t}{t})$  satisfies an LDP as  $t \rightarrow \infty$  with rate function  $V^*(x)$ .

# Sketch proof of Cramér's theorem

- ▶ Cramér upper bound proved using a simple Chebychev argument:

$$\mathbb{P}(\bar{S}_n \geq x) = \mathbb{E}(1_{\{S_n \geq nx\}}) \leq \mathbb{E}(e^{-\theta nx} e^{\theta S_n}) = e^{-n\theta x} e^{nV(\theta)}.$$

We then tighten the bound by taking the inf over  $\theta$  on the right hand side:

$$\mathbb{P}(\bar{S}_n \geq x) \leq e^{-n \sup_{\theta} [\theta x - V(\theta)]} = e^{-nV^*(x)}.$$

- ▶ Lower bound is obtained by changing to a different measure  $\mathbb{P}_{\theta^*(x)}$  under which  $\{\bar{S}_n \geq x\}$  is no longer a rare, large deviation event.

# Sanov's theorem

- ▶ Let  $(X_i)$  be a sequence of  $n$  i.i.d. random variables in  $\mathbb{R}$  with common probability measure  $\mu$ . The sample distribution:

$$L^n = \frac{1}{n} \sum_{i=1}^n \delta_{X_i}$$

is a random probability measure (a.k.a. the *empirical measure*).


- ▶ Let  $P_n = \mu^n \circ (L^n)^{-1}$  denote the distribution of  $L^n$ , where  $\mu^n$  is the product measure.  $P_n$  is a probability measure on  $(\mathcal{P}(\mathbb{R}), \mathcal{B}(\mathcal{P}(\mathbb{R})))$  - i.e.  $P_n \in \mathcal{P}(\mathcal{P}(\mathbb{R}))$ . By SLLN, we can show that  $P_n \xrightarrow{w} \delta_\mu$ .
- ▶ **Theorem** (Sanov).  $(L^n)$  satisfies an LDP in the topology of weak convergence<sup>1</sup> as  $n \rightarrow \infty$  with rate function given by the infinite dimensional counterpart of  $V^*(x)$ :

$$R(\nu|\mu) = \sup_{p \in B(\mathbb{R})} \left[ \int p d\nu - \log \int e^p d\mu \right],$$

where  $B(\mathbb{R})$  is the space of bounded, measurable functions on  $\mathbb{R}$ .

(see [Var10]), so  $\mathbb{P}(L^n \in A) \approx e^{-n \inf_{\nu \in A} R(\nu|\mu)}$  for  $\mu \notin A$ .

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<sup>1</sup>  $A \subseteq \mathcal{P}(\mathbb{R})$  is closed iff for any  $(\mu_n) \in A$  with  $\mu_n \xrightarrow{w} \mu \in \mathcal{P}(\mathbb{R})$ , we have  $\mu \in A$ . 

By solving the variational problem on the previous slide, we can show that the rate function simplifies to

$$R(\nu|\mu) = \begin{cases} \int_{-\infty}^{\infty} (\log \frac{d\nu}{d\mu}) d\nu = \int_{-\infty}^{\infty} \frac{d\nu}{d\mu} (\log \frac{d\nu}{d\mu}) d\mu & \text{if } (\nu \ll \mu), \\ \infty & \text{otherwise} \end{cases}$$



# The Brownian sheet

- ▶ Let  $(Z_t)$  be the *Brownian sheet*, i.e. the centred Gaussian process on  $[0, 1]^2$  with zero mean and covariance structure

$$\mathbb{E}(Z_t Z_s) = (s_1 \wedge t_1)(s_2 \wedge t_2)$$

where  $t = (t_1, t_2)$ ,  $s = (s_1, s_2)$ .  $Z$  is a “two-parameter” Brownian motion.

- ▶ Then  $\sqrt{\epsilon} Z$  satisfies the LDP on  $C_0([0, 1]^2)$  with rate function

$$I(f) = \begin{cases} \frac{1}{2} \int_{[0,1]^2} \left( \frac{\partial^2 f}{\partial s \partial t} \right)^2 ds dt & \text{if } \frac{\partial^2 f}{\partial s \partial t} \in L^2, \\ +\infty & \text{otherwise.} \end{cases}$$

# Saddlepoint approximations

The LDP gives crude exponential bounds. For a Lévy process  $(X_t)$  with density  $p_t(x)$ , we can sharpen these bounds using saddlepoint methods, proved using contour integration:

- **Large-time estimate**

$$p_t(xt) \sim \frac{e^{-t(p^*x - V(p^*))}}{\sqrt{2\pi t V''(p^*)}} = \frac{e^{-tV^*(x)}}{\sqrt{2\pi t V''(p^*)}} \quad (t \rightarrow \infty)$$

(see F-López, Forde & Jacquier [FLFJ11]).

- **Tail estimate**

$$p_t(x) \sim \frac{e^{-p^*(\frac{x}{t})x + tV(p^*(\frac{x}{t}))}}{\sqrt{2\pi t V''(p^*(\frac{x}{t}))}} \quad (x \rightarrow \infty).$$

(see F-López, Forde [FLF11]).  $p^* = p^*(x)$  is the unique solution to the saddlepoint equation  $V'(p^*) = x$ .

- Similar saddlepoint estimates can be obtained for the well known **Heston** stochastic volatility model for large-time [FJ09], [FJM10], small-time [FJL10] and tail regimes (see Friz et al. [FGGS10]).

# Saddlepoint methods in infinite dimensions - the Feynman path integral

- ▶ Consider the Feynman path integral for a **wavefunction**  $\psi(x, t)$ :

$$\begin{aligned}\psi(x, t) &= (2\pi i)^{-\frac{n}{2}} \int_{\gamma: \gamma_t = x} e^{\frac{i}{\hbar} [\frac{1}{2} m \int_0^t \dot{\gamma}^2 d\tau - \int_0^t V(\gamma_\tau) d\tau]} \psi(\gamma_0, 0) \mathcal{D}\gamma \\ &= (2\pi i)^{-\frac{n}{2}} \int_{\mathcal{H}} e^{-\frac{i}{2} \frac{m}{\hbar} \int_0^t \dot{\gamma}^2 d\tau} d\mu(\gamma)\end{aligned}$$

for  $x \in \mathbb{R}^n$ , with  $\psi(x, 0) = e^{\frac{i}{\hbar} f(y)} \chi(y)$ .

- ▶ The first line is the formal expression for the path integral which we define rigorously via the **Fresnel integral** in the second line over  $\mathcal{H} = \{\gamma \in C[0, t] : \dot{\gamma} \in L^2[0, t], \gamma_t = x\}$  for  $V, \psi(\cdot, 0) \in \mathcal{F}(\mathcal{H})$ .
- ▶  $f(\gamma) = e^{-\frac{i}{\hbar} \int_0^t V(\gamma_\tau) d\tau} \psi(\gamma_0, 0)$  is the Fourier transform:

$$f(\gamma) = \int_{\mathcal{H}} e^{(\gamma, \gamma_1)} d\mu(\gamma_1)$$

of  $\mu \in \mathcal{M}(\mathcal{H})$  with B.V., where  $(\gamma, \gamma_1) = \frac{m}{\hbar} \int_0^1 \dot{\gamma} \dot{\gamma}_2 d\tau$ , [AHM08]<sup>2</sup>.

- ▶  $\psi(x, t)$  satisfies the **Schrödinger eq**:  $i\hbar \frac{\partial \psi}{\partial t} = -\frac{\hbar^2}{2m} \Delta \psi + V(x) \psi$ .

<sup>2</sup>Feynman integral can also be defined via analytic continuation of Wiener measure.

# Letting $\hbar \rightarrow 0$ - the semi-classical expansion

- ▶ The integrand  $e^{\frac{i}{\hbar} S_t} = e^{\frac{i}{\hbar} [\frac{1}{2} m \int_0^t \dot{\gamma}^2 d\tau - \int_0^t V(\gamma_\tau) d\tau]}$  is an infinite-dimensional oscillatory integral. If we let  $\hbar \rightarrow 0$ , we tend towards classical everyday Newtonian mechanics and the integral becomes highly oscillatory, so we expect the main contribution to come from the classical path  $\gamma^*$  which make  $S_t$  stationary (in analogy with the finite-dimensional *method of stationary phase*).
- ▶ From this we can compute the *semi-classical expansion*:

$$\psi(x, t) \sim (2\pi i)^{-\frac{n}{2}} \frac{1}{\sqrt{\det(\dots)}} e^{\frac{i}{\hbar} [\frac{1}{2} m \int_0^t (\dot{\gamma}^*)^2 d\tau - \int_0^t V(\gamma_\tau^*) d\tau]} \chi(y)$$

as  $\hbar \rightarrow 0$  (see [AHM08]).

- ▶ The stationary path  $\gamma^*$  is just the classical path  $m\ddot{\gamma} = -\nabla V$  followed by a particle moving under the potential  $V(x)$ , which goes from  $y$  to  $x$  in time  $t$  with initial momentum  $f'(y)$  (IF there is a unique non-degenerate stationary path  $\gamma^*$  with this property).

# The Donsker-Varadhan LDP for the occupation measure of the Ornstein Uhlenbeck process

Let  $dY_t = -\theta Y_t dt + dW_t$  be an OU process for  $\theta > 0$ . Let


$$\mu_t(A) = \frac{1}{t} \int_0^t 1_A(Y_s) ds$$

denote the proportion of time that  $Y$  spends in  $A$ , for  $A \in \mathcal{B}(\mathbb{R})$ . For each  $t > 0$  and  $\omega$ ,  $\mu_t(\omega, \cdot) \in \mathcal{P}(\mathbb{R})$ . Then from [DV76] (or [Str84])  $\mu_t(\cdot)$  satisfies the LDP as  $t \rightarrow \infty$  in the topology of weak convergence, with a good<sup>3</sup>, convex, lower semicontinuous rate function given by:

$$I_B(\mu) = - \inf_{u \in \mathcal{D}^+} \int_{-\infty}^{\infty} \frac{Lu}{u} d\mu$$

where  $L = -\theta y \frac{d}{dy} + \frac{1}{2} \frac{d^2}{dy^2}$  is the infinitesimal generator for  $Y$  and  $\mathcal{D}^+$  is the set of  $u$  in the domain  $\mathcal{D}$  of  $L$  with  $u > \epsilon$  for some  $\epsilon > 0$ .

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<sup>3</sup>good means that the level set  $\{x : I(x) \leq \alpha\}$  is compact. 

# Simplifying the rate function

- ▶ We can simplify  $I_B$  to the following:

$$I_B(\mu) = \frac{1}{2} \int_{-\infty}^{\infty} \left| \partial_y \sqrt{\frac{d\mu}{d\mu_\infty}}(y) \right|^2 \mu_\infty(dy)$$

for  $\mu \ll \mu_\infty$ , where  $\mu_\infty(y) = \left(\frac{\theta}{\pi}\right)^{\frac{1}{2}} e^{-\theta y^2}$  is the unique stationary distribution for  $Y$ , i.e.  $N(0, 1/(2\theta))$ .  $\frac{d\mu}{d\mu_\infty}$  is the Radon-Nikodým derivative. If  $\mu$  is not absolutely cts wrt  $\mu_\infty$ , then  $I_B(\mu) = \infty$ .

- ▶  $\mathcal{P}(\mathbb{R})$  can be made into a (non-compact) metric space using the **Prokhorov metric**.
- ▶  $I_B(\mu)$  clearly attains its minimum value of zero at  $\mu = \mu_\infty$ , and we can show that  $\mu_\infty$  is the unique minimizer of  $I_B(\mu)$

# An uncorrelated Stochastic volatility model

- ▶ Consider a stochastic volatility model for a log stock price process  $X_t = \log S_t$ :

$$\begin{cases} dX_t = -\frac{1}{2}\sigma^2(Y_t)dt + \sigma(Y_t)dW_t^1, \\ dY_t = -\theta Y_t dt + dW_t^2 \end{cases} \quad (1)$$

for  $\theta > 0$ , where  $f(y) = \sigma^2(y)$  is a continuous non-decreasing function with  $0 < f_{\min} \leq f(y) \leq f_{\max}$  and  $d\langle W_1, W_2 \rangle = 0$  with  $x_0 = 0$ .

- ▶ The distribution of  $X_t$ , *conditional* on  $A_t = \frac{1}{t} \int_0^t \sigma^2(Y_s)ds$ , is  $N(-\frac{1}{2}A_t t, A_t t)$ .

# Using the contraction principle

- ▶ Let  $F(\mu) = \int_{-\infty}^{\infty} f(y)\mu(dy)$  for  $\mu \in \mathcal{P}(\mathbb{R})$ . Then we can re-write  $A_t$  as

$$A_t = F(\mu_t) = \int_{-\infty}^{\infty} f(y)\mu_t(dy) = \frac{1}{t} \int_0^t f(Y_s)ds.$$

- ▶  $F : \mathcal{P}(\mathbb{R}) \mapsto [f_{\min}, f_{\max}]$  is a bounded, continuous functional <sup>4</sup>, because if  $\mu_n \xrightarrow{w} \mu$  then  $\int f(y)\mu_n(dy) \rightarrow \int f(y)\mu(dy)$ , because  $f \in C_b$ .
- ▶ Thus, by the *contraction principle* from large deviations theory,  $A_t$  also satisfies the LDP, with rate function

$$I_f(a) = \inf_{\mu \in \mathcal{P}(\mathbb{R}) : F(\mu) = a} I_B(\mu) \quad , \quad a \in [f_{\min}, f_{\max}]. \quad (2)$$

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<sup>4</sup>in the topology of weak convergence.



# A joint LDP for $(X_t/t, A_t)$

**Proposition** [Forde11a].  $(X_t/t, A_t)$  satisfies a LDP on  $\mathbb{R} \times [f_{\min}, f_{\max}]$  as  $t \rightarrow \infty$  with rate function

$$I(x, a) = aV^*\left(\frac{x}{a}\right) + I_f(a)$$

where  $V^*(x) = \frac{1}{2}(x + \frac{1}{2})^2$ .

**Sketch proof.** Let  $Z_t = X_t/t$ . We first note that  $(Z_t, A_t) \stackrel{d}{=} (\frac{1}{t}W_{tA_t} - \frac{1}{2}A_t, A_t)$ . Conditioning on  $A_t$ , formally we have

$$\mathbb{P}(|Z_t - x| < \delta, |A_t - a| < \delta) \approx (\cdot) \times e^{-aV^*(\frac{x}{a})/t} e^{-I_f(a)/t}$$

as  $t \rightarrow \infty$ , where  $aV^*(\frac{x}{a})$  is the rate function of  $W_{ta} - \frac{1}{2}a$ , for  $a$  fixed. This argument can be made rigorous.

- **Corollary** [Forde11a].  $(X_t/t)$  satisfies the LDP as  $t \rightarrow \infty$  with a good rate function given by

$$I(x) = \inf_{a \in [f_{\min}, f_{\max}]} \left\{ \frac{(x + \frac{1}{2}a)^2}{2a} + I_f(a) \right\} \leq \frac{(x + \frac{1}{2}\bar{\sigma}^2)^2}{2\bar{\sigma}^2} \quad (3)$$

**Proof** The LDP with a good rate function just follows from the contraction principle.

- This can be applied to price call options with value  $\mathbb{E}(e^{X_t} - K)^+$ .
- We can relax the assumption that  $\sigma$  is bounded to a **sublinear** growth condition  $\sigma(y) \leq A(1 + |y|^p)$ ,  $A > 0, p \in (0, 1)$ ; in this case we take the infimum over all  $a \in (0, \infty)$  in (3) (see [Forde11b]).
- The LDP can be also be extended to a Lévy process or a CEV process evaluated the OU time-change  $\int_0^t f(Y_s)ds$ .

For the case of sublinear growth, the following lemma is the key observation:

**Lemma.** If  $I_B(\mu) \leq \alpha$  and  $k \in (0, 1)$ , we have

$$\int_{-\infty}^{\infty} y^2 \mu(dy) \leq \frac{\alpha + k}{2k(1 - k)}.$$

**Proof.** If we consider the test function  $u = e^{ky^2}$  in  $I_B(\mu) = -\inf_{u \in \mathcal{D}^+} \int_{-\infty}^{\infty} \frac{Lu}{u} d\mu$ , then  $-\frac{Lu}{u}(y) = k[2(1 - k)y^2 - 1]$ . From this we obtain

$$\begin{aligned} \alpha \geq I_B(\mu) &= -\inf_{u \in \mathcal{D}^+} \int_{-\infty}^{\infty} \frac{Lu}{u} d\mu = \sup_{u \in \mathcal{D}^+} -\int_{-\infty}^{\infty} \frac{Lu}{u} d\mu \\ &\geq \int_{-\infty}^{\infty} k[2(1 - k)y^2 - 1] \mu(dy) \\ &= 2k(1 - k) \int_{-\infty}^{\infty} y^2 \mu(dy) - k. \end{aligned}$$

# The CEV model

- ▶ The CEV model is defined by the SDE

$$dS_t = \delta S_t^\beta dW_t \quad (4)$$

with  $\beta \in (0, 1)$ ,  $\delta > 0$  and  $S = 0$  absorbing so  $(S_t)$  is a martingale.

- ▶ The transition density is

$$p(t, S_0, S) = \frac{S^{-2\bar{\beta} - \frac{3}{2}} S_0^{\frac{1}{2}}}{\delta^2 |\bar{\beta}| t} \exp\left(-\frac{S_0^{-2\bar{\beta}} + S^{-2\bar{\beta}}}{2\delta^2 \bar{\beta}^2 t}\right) I_\nu\left(\frac{S_0^{-\bar{\beta}} S^{-\bar{\beta}}}{\delta^2 \bar{\beta}^2 t}\right) \quad (S > 0), \quad (5)$$

where  $\bar{\beta} = \beta - 1$ ,  $\nu = \frac{1}{2|\bar{\beta}|}$ , and  $I_\nu(\cdot)$  is the modified Bessel function of the first kind (see [DavLin01]).

- ▶ **Proposition.** Let  $\gamma = 1/|\bar{\beta}|$ . Then using (5) we can show that  $(S_t/t^\gamma)$  satisfies the LDP on  $[0, \infty)$  as  $t \rightarrow \infty$  with continuous rate function

$$I_{\text{CEV}}(K) = \frac{K^{2|\bar{\beta}|}}{2\delta^2 \bar{\beta}^2} \quad (K \geq 0).$$

# The CEV-Heston model

- Combining the CEV model with a CIR time-change, we can define the uncorrelated *CEV-Heston model*, governed by the following SDEs

$$\begin{cases} dS_t = S_t^\beta \sqrt{Y_t} dW_t^1, \\ dY_t = \kappa(\theta - Y_t)dt + \sigma\sqrt{Y_t}dW_t^2 \end{cases}$$

with  $dW_t^1 dW_t^2 = 0$ ,  $Y_0 = y_0 > 0$ .

- Conditioning on  $\int_0^t Y_s ds$ , we can write  $S_t = X_{\int_0^t Y_s ds}$ , where  $X$  is now just the standard CEV process  $dX_t = \delta X_t^\beta dW_t$  with  $\delta = 1$ .
- By a similar argument to that used for the OU model, we have:  
**Proposition.**  $(S_t/t^\gamma)$  satisfies the LDP on  $[0, \infty)$  as  $t \rightarrow \infty$  with a good rate function given by

$$I_{\text{CEVH}}(K) = \inf_{a \in (0, \infty)} [a I_{\text{CEV}}(\frac{K}{a^\gamma}) + I_{\text{CIR}}(a)] \leq \theta I_{\text{CEV}}(\frac{K}{\theta^\gamma}) \quad (K \geq 0),$$

where  $I_{\text{CIR}}(a)$  is the rate function of  $A_t = \frac{1}{t} \int_0^t Y_s ds$ , and the infimum of  $I$  is attained uniquely at  $K = 0$ , where  $I(K) = 0$ .

# Call options

- ▶ We can show that call options have the same large-time behaviour

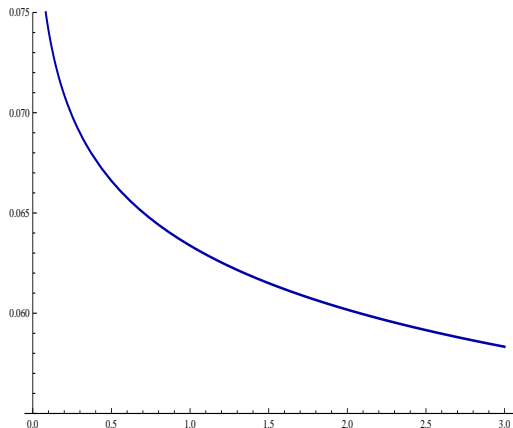
$$\lim_{t \rightarrow \infty} \frac{1}{t} \log \mathbb{E}(S_t - Kt^\gamma)^+ = I_{\text{CEVH}}(K).$$

- ▶ For the large-time, fixed-strike regime, we can show that

$$S_0 - \mathbb{E}(S_t - K)^+ = cK (\theta t)^{-\frac{\gamma}{2}} (1 + o(1)) \quad (t \rightarrow \infty)$$

where  $c = \frac{1}{\Gamma(1+\frac{\gamma}{2})} \left[ \frac{1}{2} \left( \frac{S_0^{-2\tilde{\beta}}}{\delta^2 \beta^2} \right) \right]^{\frac{\gamma}{2}}.$

# The large-maturity smile for the CEV-Heston model



**Figure:** Here we have plotted the implied volatility for the CEV-Heston model in the large-time, large-strike regime for  $t = 30$  years using Corollary 7.1 in Gao&Lee[GL11], with  $\delta = 1, \beta = .7, S_0 = 1$  and  $\kappa = 1.15, \theta = .04, \sigma = 0.2$ . Working in the large-time, large-strike parameterization allows us to see the slope and the *convexity* effect.

# The Maximum likelihood estimator of $\theta$ for the OU process

- ▶ Let  $\theta_0$  denote the true value of  $\theta$ .
- ▶ Let  $\mathbb{P}_\theta^T$  be the measure induced on  $(\mathcal{C}[0, T], \mathcal{B}(\mathcal{C}[0, T]))$  by the solution of  $dY_t = -\theta Y_t dt + dW_t$ . Then, from Girsanov's theorem, we have the likelihood ratio

$$L(\theta) = \frac{d\mathbb{P}_\theta^T}{d\mathbb{P}_0^T} = e^{-\int_0^T \theta Y_t dY_t - \frac{1}{2} \int_0^T \theta^2 Y_t^2 dt} \quad (6)$$

(note that  $\mathbb{P}_0^T$  is just the Wiener measure).

- ▶ Taking the log of  $L(\theta)$ , differentiating wrt  $\theta$  and setting to zero, we obtain the classical maximum likelihood estimator for  $\theta$ :

$$\hat{\theta}_T = -\frac{\int_0^T Y_t dY_t}{\int_0^T Y_t^2 dt},$$

(see [Kut04]) and  $\hat{\theta}_T$  is a consistent estimator of  $\theta_0$  (i.e.  $\hat{\theta}_T \rightarrow \theta_0$  in probability as  $T \rightarrow \infty$ ).



# Large deviations for $\hat{\theta}_T$

It can be shown (see [FLP99]) that  $\hat{\theta}_T$  satisfies the LDP with good rate function

$$J(\theta) = \begin{cases} \frac{1}{4\theta}(\theta - \theta_0)^2 & (\theta \geq \frac{1}{3}\theta_0), \\ -2\theta + \theta_0 & (\theta < \frac{1}{3}\theta_0). \end{cases}$$

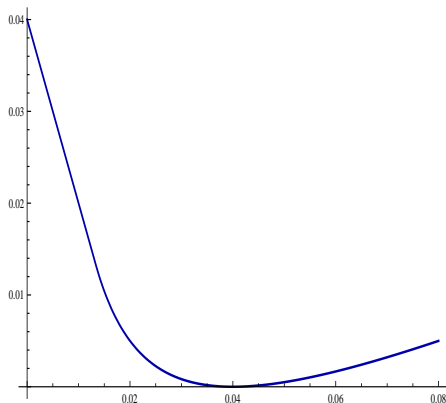


Figure: Here we have plotted  $J(\theta)$  for  $\theta_0 = 0.04$ .

- Consider the *stochastic* heat equation with small-noise:

$$\partial_t u_{t,x}^\epsilon = \frac{1}{2} \partial_{xx} u_{t,x}^\epsilon + \sqrt{\epsilon} \dot{W}_{t,x} \quad (7)$$

on  $[0, T] \times [0, 1]$ , with Dirichlet boundary condition  $u_{0,\cdot}^\epsilon \in C^{2\alpha}$ ,  $0 \leq \alpha < \frac{1}{4}$  and  $u_{t,0}^\epsilon = u_{t,1}^\epsilon = 1$ .  $\dot{W}$  is *space-time white noise*, which is a Gaussian random set function such that  $W_A \sim N(0, \text{Leb}(A))$  for  $A \in \mathcal{B}([0, T] \times [0, 1])$  and  $\mathbb{E}(W_A W_B) = \text{Leb}(A \cap B)$ .

- $W_{t,x} := W_{[0,t] \times [0,x]}$  is the previously defined Brownian sheet.
- We can give a rigorous meaning to (7) by writing the solution in the integrated form

$$u_{t,x}^\epsilon = \int_0^1 G_t(x, y) u_0(y) dy + \sqrt{\epsilon} \int_0^t \int_0^1 G_{t-s}(x, y) W(ds, dy)$$

where the stochastic integral on the right is defined in a similar way to the classical Itô integral, and  $G_t(x, y)$  is the usual Green kernel for the non-stochastic heat eq  $\partial_t u = \frac{1}{2} \partial_{xx} u$  with the same Dirichlet boundary condition (see Pardoux[Par93]).

# Large deviations for the stochastic heat equation

- ▶ The *skeleton* of  $h = h(t, x)$  in the Cameron-Martin space for  $W$  is given by

$$Z_{t,x}^h = \int_0^1 G_t(x, y) u_0(y) dy + \sqrt{\epsilon} \int_0^t \int_0^1 G_{t-s}(x, y) \frac{\partial^2 h}{\partial t \partial x}(s, y) ds dy .$$







- ▶ By a generalized contraction principle,  $u^\epsilon$  satisfies the LDP on  $\chi = C^{\alpha,0}([0, T] \times [0, 1])$  with rate function

$$S(f) = \begin{cases} \inf \{ I(h) : Z^h = f \} , & f \in \text{Im}(Z) \\ +\infty & (\text{otherwise}) \end{cases} \quad (8)$$








(see [CM07]), where  $I(h) = \frac{1}{2} \int_{[0,1]^2} \left( \frac{\partial^2 h}{\partial s \partial t} \right)^2 ds dt$  is the previously defined rate function for the Brownian sheet.








- ▶ We can also compute a small-noise LDP for the alternative way of approaching SPDEs as a Hilbert-space valued SDE driven by a Hilbert-spaced valued Brownian motion (see [DPZ92]).

# References

-  Albeverio, S., Hoegh-Krohn, R. and S. Mazzuchi, “Mathematical theory of Feynman path integrals. An introduction”, Second edition. Lecture Notes in Mathematics, 523. Springer Verlag, Berlin, 2008.
-  Chenal, F. and A. Millet, “Uniform large deviations for parabolic SPDEs and applications”, *Stochastic Processes and their Applications*, 72, 161-186, 2007.
-  Davydov, D. and V. Linetsky, “The Valuation and Hedging of Barrier and Lookback Options under the CEV Process,” *Management Science*, 47, 949-965, 2001.
-  Da Prato, G. and J. Zabczyk, ‘Stochastic equations in infinite dimensions’, Cambridge University Press, 1992, XVIII.
-  Donsker, M.D. and S.R.S Varadhan, “Asymptotic evaluation of Markov process expectations for large time, III”, *Comm. Pure Appl. Math.*, 29, pp.389-461 (1976).
-  P. Friz, S. Gerhold, A. Gulisashvili, S. Sturm, “On refined volatility smile expansion in the Heston model”, forthcoming in *Quantitative Finance*.

# References

-  Figueroa-López, J., M.Forde and A.Jacquier, “The large-time smile and skew for exponential Lévy models”, (2011), submitted.
-  Forde, M., A.Jacquier and A.Mijatović (2010), “Asymptotic formulae for implied volatility in the Heston model”, *Proc. R. Soc. A*, 466, 3593-3620, 2010.
-  Forde, M., “Large-time asymptotics for an uncorrelated stochastic volatility model”, (2011), to appear in *Statistics and Probability Letters*.
-  Forde, M., “Large-time asymptotics for general stochastic volatility and time-changed Lévy models”, (2011), submitted.
-  Forde, M., Forde, M. and A.Jacquier, “The large maturity smile for the Heston model” (2009), forthcoming in *Finance and Stochastics*.
-  M.Forde, A.Jacquier and R.Lee , “The small-time smile and term structure of implied volatility for the Heston model”, (2010).
-  Figueroa-López, J. and M.Forde, “Sharp tail estimates for exponential Lévy models”, (2011).

-  Florens-Landais, D. and H. Pham, “Large deviations in estimation of an Ornstein Uhlenbeck model”, *J. Appl. Prob.*, **36**, 60-77 (1999).
-  Gao, K., and R. Lee, “Asymptotics of Implied Volatility in Extreme Regimes”, 2011, preprint.
-  Kutoyants Yu. A., “Statistical Inference for Ergodic Diffusion Processes”, Springer Series in Statistics, London, 2004, 496p.
-  Pardoux, E., “Stochastic Partial Differential Equations, a review”, *Bull. Sc. Math.*, 117, 29-47, 1993.
-  Stroock, D.W. “An introduction to the theory of large deviations”, Springer-Verlag, Berlin, (1984).
-  Varadhan, S.R.S., “Large deviations” lecture notes at NYU, Spring 2010.
-  Walsh, J., “An introduction to stochastic partial differential equations”, in *École d’été de Probabilité de Saint Flour XIV, LNM*, 1180, 265-439, Springer, 1986.