## EXAM STOCHASTIC DIFFERENTIAL EQUATIONS (3TU) – SOLUTIONS May 30, 2011

Grading:  $2 + (1+1\frac{1}{2}) + 1\frac{1}{2} + 2 + 2$ 

1. Since  $\sigma(\gamma_1)$  is the collection of all sets of the form  $\{\gamma_1 \in A\}$  with A a Borel set in  $\mathbb{R}$ , we must show that

$$\int_{\{\gamma_1 \in A\}} 1_{\{\gamma_1 \ge \gamma_2\}} dP = \int_{\{\gamma_1 \in A\}} \Psi(\gamma_1) d\mathbb{P}$$

By independence, the joint density of  $(\gamma_1, \gamma_2)$  is given by

$$f_{(\gamma_1,\gamma_2)}(x_1,x_2) = f_{\gamma_1}(x_1)f_{\gamma_2}(x_2) = \frac{1}{2\pi}\exp(-\frac{1}{2}x_1^2)\exp(-\frac{1}{2}x_2^2)$$

and therefore

$$\begin{split} \int_{\{\gamma_1 \in A\}} \mathbf{1}_{\{\gamma_1 \geq \gamma_2\}} \, dP &= \frac{1}{2\pi} \int_A \int_{-\infty}^{x_1} \exp(-\frac{1}{2}x_1^2) \exp(-\frac{1}{2}x_2^2) \, dx_2 \, dx_1 \\ &\frac{1}{\sqrt{2\pi}} \int_A \Psi(x_1) \exp(-\frac{1}{2}x_1^2) \, dx_1 = \int_{\{\gamma_1 \in A\}} \Psi(\gamma_1) \, d\mathbb{P}. \end{split}$$

2. a) First we check integrability. We have

$$\mathbb{E}|e^{\eta_n}| = \mathbb{E}e^{\eta_n} = p\sum_{k=1}^{\infty} e^k (1-p)^{k-1} = pk\sum_{j=0}^{\infty} e^j (1-p)^j$$

and this sum is (absolutely) if and only if  $1 - p < \frac{1}{e}$ , that is,  $1 - \frac{1}{e} .$  $Hence, by independence, the <math>\xi_n$  are integrable (for all  $a \in \mathbb{R}$ ) if and only if  $1 - \frac{1}{e} . Next, for these <math>p$ ,

$$\mathbb{E}(\xi_n | \mathcal{F}_{n-1}) = e^{\eta_1 + \dots + \eta_{n-1} - (n-1)a} e^{-a} \mathbb{E}(e^{\eta_n} | \mathcal{F}_{n-1}) = \xi_{n-1} e^{-a} \mathbb{E}e^{\eta_n}$$

since  $e^{\eta_1 + \dots + \eta_{n-1} - (n-1)a} = \xi_{n-1}$  is  $\mathcal{F}_{n-1}$ -measurable and  $e^{\eta_n}$  is independent of  $\mathcal{F}_{n-1}$ . Thus we find  $\mathbb{E}(\xi_n | \mathcal{F}_{n-1}) = \xi_{n-1}$  if and only if  $\mathbb{E}e^{\eta_n} = e^a$ , that is, if and only if

$$e^{a} = pk \sum_{j=0}^{\infty} e^{j} (1-p)^{j} = \frac{ep}{1-e(1-p)},$$

that is,  $a = \ln \frac{ep}{1 - e(1 - p)}$ .

b) Almost sure convergence is immediate from  $L^1$ -boundedness (note that  $\xi_n \ge 0$ , so  $\mathbb{E}|\xi_n| = \mathbb{E}\xi_n = \mathbb{E}\xi_1$ ) by the martingale convergence theorem.

Pointwise, the convergence implies that either  $\eta_1 + \cdots + \eta_n - na \to -\infty$ (in which case the exponential converges to 0) or that  $\eta_1 + \cdots + \eta_n - na$ converges to a finite limit. If the latter happens with positive probability, it would imply that  $\eta_n \to a$  with positive probability; this is a contradiction since  $\eta_n$  can take any integer value with finite probability independent of n. It follows that we must have  $\eta_1 + \cdots + \eta_n - na \to -\infty$ , so  $\xi_n \to 0$  almost surely. But  $\mathbb{E}\xi_n = \mathbb{E}\xi_1 \neq 0$ , so we do not have  $L^1$ -convergence. 3. Since  $M_n$  is a submartingale, for all N we have

$$\mathbb{E}(1_{\tau \le N} M_{\tau}) = \sum_{n=0}^{N} \mathbb{E}(1_{\{\tau=n\}} M_n) \le \sum_{n=0}^{N} \mathbb{E}(1_{\{\tau=n\}} M_N) = \mathbb{E} M_N,$$

where the used the definition of a submartingale along with the fact that  $\{\tau = n\}$  belongs to  $\mathcal{F}_n$  in order to get the inequality. By monotone convergence (this uses the nonnegativity), the left-hand side converges to  $\mathbb{E}M_{\tau}$ , and the result follows by letting  $N \to \infty$ .

The game  $M_n$ , being a submartingale, is favourable to you. So your win more when you play indefinitely than when you stop.

4. From  $\int_0^T B_t dB_t = \frac{1}{2} \left( B_T^2 - T \right)$  we see

$$B_T^2 = T + 2 \int_0^T B_t, \, dB_t.$$

Now Itô's formula for  $Y_t := tB_t^2$  gives

$$Y_T = TB_T^2 = \int_0^T B_t^2 \, dt + 2 \int_0^T tB_t \, dB_t + \int_0^T t \, dt$$

and therefore

$$G = \int_0^T B_t^2 dt = T B_T^2 - \frac{T^2}{2} - 2 \int_0^T t B_t dB_t$$
  
=  $T \left( T + 2 \int_0^T B_t dB_t \right) - \frac{T^2}{2} - 2 \int_0^T t B_t dB_t$   
=  $\frac{T^2}{2} + \int_0^T 2 (T - t) B_t dB_t$ 

This gives  $g(t) = 2(T-t)B_t$ .

5. Note first that  $Y_t = y_0 e^{rt}$ , so  $\tilde{X}_t = y_0^{-1} e^{-rt} X_t$ . Since  $de^{-rt} X_t = -re^{-rt} X_t dt + e^{-rt} dX_t = e^{-rt} X_t [(\mu - r) dt + \sigma dB_t]$ , we may conclude that

$$d\tilde{X}_t = \sigma \tilde{X}_t \left[ \frac{\mu - r}{\sigma} dt + dB_t \right] = \sigma \tilde{X}_t d\tilde{B}_t$$

where  $\tilde{B}_t = B_t + \frac{\mu - r}{\sigma} t$ . Let  $\mathbb{Q}$  be the measure defined by

$$\mathbb{Q}(A) = \mathbb{E}_{\mathbb{P}}\left[1_A \exp\left(-\frac{\mu - r}{\sigma}B_T - \left(\frac{\mu - r}{\sigma}\right)^2 \frac{T}{2}\right)\right].$$

It follows from Girsanov's theorem that  $(\tilde{B}_t)_{t\geq 0}$  is standard Brownian motion, which implies that  $(\tilde{X}_t)_{t\geq 0}$  is a Q-martingale.

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