

# 1 Note on exponential-affine stock prices

The idea is to specify the dividend yield  $\delta$  and short rate  $r$  to be affine in  $X$  where  $X$  is an affine diffusion under the risk-neutral measure. Then the stock price is guessed to be exponential affine. To show that the guess works, I have to show that the guess satisfies

$$P(t) = E_t^* \left[ \int_t^\infty e^{-\int_t^s r(u)du} \delta(s) P(s) ds \right], \quad (1)$$

where  $E^*$  denotes expectation under the risk-neutral measure. The following simple example with a normally distributed dividend yield, zero short rate and zero market prices of risk illustrates that the functional form result applies. Backshi and Chen (1997, JFE) compute exponential-affine stock prices for the case where  $X$  is a square-root process.

PROPOSITION: Assume that the short rate is zero,  $r = 0$  (in the notation of the paper  $r_0 = 0$  and  $r_X = 0$ ). The dividend yield is  $\delta = X$  (in the notation of the paper,  $\delta_0 = 0$  and  $\delta_X = 1$ ) where  $X$  is an OU process which solves

$$dX(t) = k(\theta - X(t))dt + \sigma dW(t).$$

Suppose  $P$  is of the form

$$P(t) = \exp\left(at + \frac{X(t)}{k}\right) \quad (2)$$

with

$$a = -\theta - \frac{1}{2} \frac{\sigma^2}{k} < 0. \quad (3)$$

then  $P$  satisfies the pricing equation (1).

PROOF OF PROPOSITION (the proof refers to a series of facts stated in section 2 of this note): Assume that the price satisfies the guess (2). We need to show that

$$\begin{aligned} P(t) &= E_t \int_t^\infty \delta(s) P(s) ds \\ &= E_t \left[ \lim_{T \rightarrow \infty} \int_t^T \delta(s) P(s) ds \right] \end{aligned} \quad (4)$$

Define

$$P^T(t) = E_t \int_t^T \delta(s) P(s) ds$$

I will show (4) in two steps. Step (i) is

$$P(t) = \lim_{T \rightarrow \infty} P^T(t) \quad (5)$$

Step (ii) is

$$\lim_{T \rightarrow \infty} P^T(t) = E_t \left[ \lim_{T \rightarrow \infty} \int_t^T \delta(s) P(s) ds \right] \quad (6)$$

Together, these two steps yield (4).

STEP (i) : I want to interchange expectation and integral,

$$P^T(t) = E_t \left[ \int_t^T P(s) \delta(s) ds \right] = \int_t^T E_t [P(s) \delta(s)] ds \quad (7)$$

For Fubini to apply, I need that

$$E_t \int_t^T |P(s) \delta(s)| ds < \infty. \quad (8)$$

Tonelli's theorem says

$$E_t \int_t^T |P(s) \delta(s)| ds = \int_t^T E_t |P(s) \delta(s)| ds \quad (9)$$

The RHS is finite, because by FACT 3:

$$\begin{aligned} E_t [|P(s) \delta(s)|] &= E_t [|\delta(s)| P(s)] \\ &= E_t [|Z(s)|] \exp \left( as + m_t(s)/k + \frac{1}{2} v_t(s)/k^2 \right) \end{aligned} \quad (10)$$

where  $Z(s) \sim N(m_t(s) + v_t(s)/k, v_t(s))$ . This expression is continuous in  $s$ .

The term beneath the integral in (7) is given by FACT 2:

$$\begin{aligned} E_t[\delta(s)P(s)] &= E_t[X(s)\exp(as + X(s)/k)] \\ &= (m_t(s) + v_t(s)/k)\exp\left(as + m_t(s)/k + \frac{1}{2}v_t(s)/k^2\right) \end{aligned}$$

Using FACT 4,

$$\begin{aligned} P^T(t) &= \int_t^T E_t[P(s)\delta(s)] ds \\ &= \int_t^T (m_t(s) + v_t(s)/k)\exp\left(as + m_t(s)/k + \frac{1}{2}v_t(s)/k^2\right) ds \\ &= -\exp\left(aT + m_t(T)/k + \frac{1}{2}v_t(T)/k^2\right) + \exp\left(at + m_t(t)/k + \frac{1}{2}v_t(t)/k^2\right). \end{aligned}$$

Since  $\lim_{T \rightarrow \infty} m_t(T) = \theta$  and  $\lim_{T \rightarrow \infty} v_t(T) = \frac{\sigma^2}{2k}$ , I have

$$\lim_{T \rightarrow \infty} \exp\left(aT + m_t(T)/k + \frac{1}{2}v_t(T)/k^2\right) = 0$$

as long as  $a < 0$ , which I assumed in (3). This leaves

$$\lim_{T \rightarrow \infty} P^T(t) = \exp\left(at + m_t(t)/k + \frac{1}{2}v_t(t)/k^2\right).$$

where I can note that  $m_t(t)/k = X(t)/k$  and  $v_t(t)/k^2 = 0$ , so that I indeed get equation (5) for our guess (2).

STEP (ii) : From step (i), I know that

$$\lim_{T \rightarrow \infty} P^T(t) = \lim_{T \rightarrow \infty} \int_t^T E_t[P(s)\delta(s)] ds$$

I want to use Fubini to argue that the RHS of the last equation is equal to the RHS of (6). For Fubini to apply, I need condition (8) for  $T = \infty$ . The same arguments go through as before, and I know that  $m_t(s)$  and  $v_t(s)$  go to constants for  $s \rightarrow \infty$ , which means that the expression in (10) goes to zero because  $a < 0$ . This completes the proof that (6) holds.

## 2 Useful facts

FACT 1. Suppose  $X$  solves

$$dX(t) = k(\theta - X(t))dt + \sigma dW(t). \quad (11)$$

starting at  $X(0) = x_0$  and for constants  $k$ ,  $\theta$  and  $\sigma$ . Then the solution to (11) is

$$\begin{aligned} X_s &= \exp(-k(s-t)) X_t + \theta(1 - \exp(-k(s-t))) \\ &\quad + \int_t^s \exp(-k(s-u)) \sigma dW(u). \end{aligned}$$

which is normal with mean

$$m_t(s) \equiv \exp(-k(s-t)) X_t + \theta(1 - \exp(-k(s-t))),$$

and variance

$$v_t(s) \equiv \frac{\sigma^2}{2k} (1 - \exp(-2k(s-t))).$$

FACT 2: Suppose  $X \sim N(m, v)$ . Then I have for any constant  $c$

$$E[Xe^{cX}] = (m + cv) \exp\left(cm + \frac{1}{2}c^2v\right).$$

This can be verified by direct computation

$$\begin{aligned} E[Xe^{cX}] &= \int X \exp(cX) \exp\left(\frac{-(X-m)^2}{2v}\right) \frac{1}{\sqrt{2\pi v}} dX \\ &= \int X \exp\left(\frac{-X^2 - m^2 + 2X(m+cv)}{2v}\right) \frac{1}{\sqrt{2\pi v}} dX \\ &= \int X \exp\left(\frac{-(X - (m+cv))^2 + 2mcv + c^2v^2}{2v}\right) \frac{1}{\sqrt{2\pi v}} dX \\ &= \int X \exp\left(mc + \frac{1}{2}c^2v\right) \exp\left(\frac{-(X - (m+cv))^2}{2v}\right) \frac{1}{\sqrt{2\pi v}} dX \end{aligned}$$

FACT 3: Suppose  $X \sim N(m, v)$ . Then we have for any constant  $c$

$$E [X | e^{cX}] = E [Y] \exp \left( cm + \frac{1}{2} c^2 v \right).$$

where  $Y \sim N(m + cv, v)$

FACT 4:

$$\begin{aligned} & \frac{d}{ds} \exp \left( as + m_t(s)/k + \frac{1}{2} v_t(s)/k^2 \right) \\ &= - (m_t(s) + v_t(s)/k) \exp \left( as + m_t(s)/k + \frac{1}{2} v_t(s)/k^2 \right) \end{aligned}$$

as long as

$$a = -\theta - \frac{1}{2} \frac{\sigma^2}{k^2}$$

PROOF OF FACT 4: Taking derivatives:

$$\begin{aligned} & \frac{d}{ds} \exp \left( as + m_t(s)/k + \frac{1}{2} v_t(s)/k^2 \right) \\ &= \left( a + \frac{\partial m_t(s)}{\partial s} \frac{1}{k} + \frac{\partial v_t(s)}{\partial s} \frac{1}{2k^2} \right) \exp \left( as + m_t(s)/k + \frac{1}{2} v_t(s)/k^2 \right) \end{aligned}$$

$$\begin{aligned} \frac{\partial m_t(s)}{\partial s} &= -k \exp(-k(s-t)) (X_t - \theta) \\ \frac{\partial v_t(s)}{\partial s} &= \sigma^2 \exp(-2k(s-t)) \end{aligned}$$

$$\begin{aligned} & a - \exp(-k(s-t)) (X_t - \theta) + \sigma^2 \exp(-2k(s-t)) \frac{1}{2k^2} \\ &= -\theta - \frac{1}{2} \frac{\sigma^2}{k^2} - \exp(-k(s-t)) (X_t - \theta) + \sigma^2 \exp(-2k(s-t)) \frac{1}{2k^2} \\ &= -(\theta + \exp(-k(s-t)) (X_t - \theta)) - \left( \frac{1 - \exp(-2k(s-t))}{2k^2} \right) \sigma^2 \\ &= -(m_t(s) + v_t(s)/k) \end{aligned}$$

### 3 Remarks

Theorem 1 of the paper states a solution of the form

$$P(t) = \exp(A(t) - B(t)X(t))$$

with coefficients (10)-(12)

$$\begin{aligned} 0 &= A'(t) - \theta k B(t) + \frac{1}{2} \sigma^2 B(t)^2 \\ 0 &= 1 - B'(t) + kB \end{aligned}$$

for  $\delta_0 = 0$  and  $\delta_X = 1$  in  $\delta = \delta_0 + \delta_X X$  and  $r_0 = 0$  (because  $r = 0$ ). Now use Restriction 2 from the paper, which sets  $B'(t) = 0$ . This implies

$$B(t) = -\frac{1}{k}.$$

and therefore

$$0 = A'(t) + \theta + \frac{1}{2} \frac{\sigma^2}{k^2}$$

This equation is solved for  $A(t) = at$  where

$$a = -\theta - \frac{1}{2} \frac{\sigma^2}{k^2}.$$