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## The Critical Price of the American Put Near Maturity in the Jump Diffusion Model\*

Aych Bouselmi<sup>†</sup> and Damien Lamberton<sup>†</sup>

**Abstract.** We study the behavior of the critical price of an American put option near maturity in the jump diffusion model when the underlying stock pays dividends at a continuous rate and the limit of the critical price is smaller than the stock price. In particular, we prove that, unlike the case where the limit is equal to the strike price, jumps can influence the convergence rate.

**Key words.** American put, Lévy processes, critical price, free boundary, jump diffusion, convergence rate

**AMS subject classifications.** 60H30, 60J75, 91G80

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**1. Introduction.** The behavior of the critical price of the American put near maturity has been deeply investigated. Its limit was characterized in the Black–Scholes model (see [5, 13]) by

$$b(T) := \lim_{t \rightarrow T} b(t) = \min\left(\frac{r}{\delta}K, K\right),$$

where  $r$  and  $\delta$  denote the interest rate and the dividend rate and  $b(t)$  is the critical price at time  $t$ .

This result was generalized to more general exponential Lévy models in [7]. In fact, denoting  $\bar{d} = r - \delta - \int (e^y - 1)^+ \nu(dy)$ ,<sup>1</sup> with  $\nu$  the Lévy measure of the underlying Lévy process, we have

$$b(T) = K \text{ if } \bar{d} \geq 0$$

and

$$b(T) = \xi \text{ if } \bar{d} < 0,$$

where  $\xi$  is the unique solution, in  $[0, K]$ , of

$$(1) \quad rK - \delta x - \int (xe^y - K)^+ \nu(dy) = 0.$$

In the Black–Scholes model, the quantity  $\bar{d}$  reduces to  $\bar{d} = r - \delta$  and we distinguish, according as  $\bar{d} > 0$ ,  $\bar{d} = 0$ , and  $\bar{d} < 0$ , different behaviors of the critical price near maturity.

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<sup>1</sup>The quantity  $\bar{d}$  is denoted by  $d^+$  in [7].

In fact, Barles et al in [1] (see also Lamberton [6]) established, in the case where  $\bar{d} > 0$  (which implies  $b(T) = K$ ), that

$$(2) \quad \frac{K - b(t)}{\sigma K} \sim_{t \rightarrow T} \sqrt{(T - t)|\ln(T - t)|},$$

where the expression  $f \sim_{t \rightarrow a} g$  (or  $f \sim_a g$ ) is equivalent to  $\lim_{t \rightarrow a} \frac{f(t)}{g(t)} = 1$ . The cases  $\bar{d} < 0$  and  $\bar{d} = 0$  were investigated by Lamberton and by Villeneuve in [14] and they obtained as follows: If  $\bar{d} = 0$  (which also implies  $b(T) = K$ )

$$\frac{K - b(t)}{\sigma K} \sim_{t \rightarrow T} \sqrt{2(T - t)|\ln(T - t)|}.$$

If  $\bar{d} < 0$  ( $b(T) < K$ ), there exists  $y_0 \in (0, 1)$ , which is characterized thanks to an auxiliary optimal stopping problem, such that

$$\frac{b(T) - b(t)}{\sigma b(T)} \sim_{t \rightarrow T} y_0 \sqrt{(T - t)}.$$

Note that  $y_0$  can also be characterized more explicitly as the solution of an equation (see [14]).

The critical price has also been studied in the jump diffusion model. In fact, Pham proved in [11] that the result (2), obtained in [1, 6], remains exactly the same in the jump diffusion model, in the case where  $\bar{d} > 0$  and  $\delta = 0$ . This remains true if  $\delta > 0$  (see [10]).

The purpose of this paper is to study the convergence rate of the critical price of the American put, in the jump diffusion model, with  $\bar{d} \leq 0$ . Considering the results of Pham in [11], we expect to obtain the same results as the study performed by Lamberton and Villeneuve in the Black–Scholes model when ( $\bar{d} = r - \delta \leq 0$ ), meaning that jumps do not have any influence on the convergence rate. Surprisingly, we obtain the expected result only for the case  $\bar{d} = 0$ . Indeed, we obtain for  $\bar{d} = 0$  (see Theorem 5.1)

$$\frac{K - b(t)}{\sigma K} \sim_{t \rightarrow T} \sqrt{2(T - t)|\ln(T - t)|},$$

and for  $\bar{d} < 0$  (see Theorem 4.7)

$$\frac{b(T) - b(t)}{\sigma b(T)} \sim_{t \rightarrow T} y_{\lambda, \beta} \sqrt{(T - t)},$$

where  $y_{\lambda, \beta}$  is a real number satisfying  $y_{\lambda, \beta} \geq y_0$ , and depending on  $\nu(\{\ln(K/b(T))\})$  we can have  $y_{\lambda, \beta} > y_0$ . This point will be discussed in more detail in section 4.3.

This study is composed of four sections. In section 1, we recall some useful results on the American put which will be used throughout this study. In section 2, we give some results on the regularity of the American put price and the early exercise premium. In section 3, we investigate the case where the limit of the critical price is far from the singularity  $K$  (we refer to this as the *regular* case). Indeed, we then have enough regularity to give an expansion of the American put price near maturity from which the critical price behavior will be deduced. The method is similar to the one used in [14] and is based on an expansion of the American put

price along parabolas. However, the possibility that the stock price jumps into a neighborhood of the exercise price produces a contribution of the local time in the expansion. Section 4 is devoted to the study of the case  $\bar{d} = 0$ . In this case  $b(T) = K$ ; hence we no longer have enough smoothness to obtain an expansion around the limit point  $(T, b(T))$ . Then we will study the behavior of the European critical price  $b_e(t)$  instead of  $b(t)$ . Thereafter, we prove that  $b(t)$  and  $b_e(t)$  have the same behavior.

**2. Preliminaries.** In the jump diffusion model, under a risk-neutral probability which is used as a *pricing* measure, the risky asset price is modeled by  $(S_t)_{t \geq 0}$ , given by

$$S_t = S_0 e^{\tilde{X}_t} \quad \text{with } \tilde{X}_t = (r - \delta)t + \sigma B_t - \frac{\sigma^2}{2}t + Z_t - t \int (e^y - 1)\nu(dy),$$

where  $r > 0$  is the interest rate,  $\delta \geq 0$  the dividend rate,  $(B_t)_{t \geq 0}$  a standard Brownian motion, and  $(Z_t)_{t \geq 0}$  a compound Poisson process and  $\nu$  its Lévy measure. We then have

$$dS_t = S_{t-} (\gamma_0 dt + \sigma dB_t + d\bar{Z}_t) \quad \text{with } \bar{Z}_t = \sum_{0 < s \leq t} (e^{\Delta Z_s} - 1) \text{ and } \gamma_0 = r - \delta - \int (e^y - 1)\nu(dy).$$

Denote by  $\mathbb{F}$  the completed natural filtration of the process  $\tilde{X}_t$  and suppose throughout this paper that the following assumptions are satisfied:

$$\sigma > 0, \quad \nu(\mathbb{R}) < \infty, \quad \int e^y \nu(dy) < \infty, \quad \text{and} \quad \bar{d} = r - \delta - \int_{y > 0} (e^y - 1)\nu(dy) \leq 0.$$

The price of an American put with maturity  $T > 0$  and strike price  $K > 0$  is given, at  $t \in [0, T]$ , by  $P(t, S_t)$  with  $P$  defined for all  $(t, x) \in [0, T] \times \mathbb{R}^+$  by

$$P(t, x) = \sup_{\tau \in \mathcal{T}_{0, T-t}} \mathbb{E} \left( e^{-r\tau} \psi(x e^{\tilde{X}_\tau}) \right) \quad \text{with } \psi(y) = (K - y)^+,$$

where  $\mathcal{T}_{0, T-t}$  is the set of all  $\mathbb{F}$ -stopping times taking values in  $[0, T - t]$ .

The value function  $P$  can also be characterized (see [7]) as the unique continuous and bounded solution of the variational inequality

$$\max \left\{ \psi - P; \frac{\partial P}{\partial t} + \mathcal{A}P - rP \right\} = 0 \quad (\text{in the sense of distributions})$$

with the terminal condition  $P(T, \cdot) = \psi$ . Here,  $\mathcal{A}$  is the infinitesimal generator of the process  $S$ . The free boundary of this variational inequality is called the exercise boundary, and at each  $t \in [0, T]$ , the critical price is given by

$$b(t) = \inf \{ x > 0 \mid P(t, x) > (K - x)^+ \}.$$

It was proved in [7] that if  $\bar{d} \leq 0$ , then

$$(3) \quad \lim_{t \rightarrow T} b(t) = \xi := b(T),$$

where  $\xi$  is the unique solution, in  $[0, K]$ , of  $rK = \delta x + \int (xe^y - K)^+ \nu(dy)$ . Note that if  $\bar{d} = 0$ , then  $b(T) = \xi = K$ .

Finally, recall that the price of a European put with maturity  $T$  and strike price  $K$  is given, at time  $t$ , by

$$P_e(t, x) = \mathbb{E} \left( e^{-r(T-t)} (K - S_{T-t})_+ \mid S_0 = x \right).$$

The quantity  $(P - P_e)$  is called the early exercise premium; we then have  $P(t, x) = P_e(t, x) + e(T - t, x)$ . Setting  $\theta = T - t$ , then the early exercise premium,  $e(\theta, x)$ , is characterized for the American put in the exponential Levy model as follows (see [10]):

$$e(\theta, x) = \mathbb{E} \left\{ \int_0^\theta e^{-rs} \times \left( rK - \delta S_s^x - \int_{y>0} [P(t+s, S_s^x e^y) - (K - S_s^x e^y)] \nu(dy) \right) 1_{\{S_s^x < b(t+s)\}} ds \right\}.$$

Here  $S_s^x = xe^{\tilde{X}_s}$ . We also define, for all  $t \in (0, T)$ , the European critical price,  $b_e(t)$ , as the unique solution of

$$F(t, x) = P_e(t, x) - (K - x) = 0.$$

It easy to check that for all  $t \in (0, T)$ ,  $b_e(t)$  is well defined,  $b_e(t) \in (0, K)$ . It is also straightforward that  $P_e \leq P$ ; therefore  $b(t) \leq b_e(t) \leq K$ .

**3. Regularity estimate for the value function in the jump diffusion model.** In this section, we study the spatial derivatives behavior of  $P$ ,  $P_e$ , and  $e(\theta, x)$  near  $(T, b(T))$ . We also give a lower bound for the second spatial derivative near  $(T, b(T))$ . These results will be proved in Appendix A.

**Lemma 3.1.** *Under the model assumption, we have the following*

1. For all  $x \in (0, b_e(t) \wedge b(T)]$ , we have, as  $\theta (= T - t)$  goes to 0,

$$\left| \frac{\partial e}{\partial x}(\theta, x) \right| = \frac{1}{x} o(\sqrt{\theta})$$

with  $o(\sqrt{\theta})$  uniform with respect to  $x$ .

2. For all  $x \in (0, b(T) \wedge b_e(t)]$ , we have

$$\frac{\partial P}{\partial x}(t, x) + 1 = \left( 1 + \frac{1}{x} \right) o(\sqrt{\theta})$$

with  $o(\sqrt{\theta})$  uniform with respect to  $x$ .

**Lemma 3.2.** *According to the hypotheses of the model, we have, for all  $b(t) \leq x < b(T) \wedge b_e(t)$  and for all  $\theta = T - t$  small enough, the following inequality:*

$$\inf_{b(t) < u < x} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \geq \left( \hat{\delta} - \epsilon(\theta) \right) (b(T) - x) - \lambda K \mathbb{E} \left( \sigma B_\theta - \ln \left( \frac{b(T)}{x} \right) \right)^+ + o(\sqrt{\theta})$$

with  $\lim_{\theta \downarrow 0} \epsilon(\theta) = 0$ ,  $\hat{\delta} = \delta + \int_{\{y > \ln(K/b(T))\}} e^y \nu(dy)$ ,  $\lambda = \nu\{\ln(\frac{K}{b(T)})\}$ .

**4. Regular case.** We begin this section by introducing an auxiliary optimal stopping problem which will be needed for deriving the expansion of the American put price near maturity along a parabolic branch. Once we have this expansion we will be able to derive the convergence rate of the critical price.

**4.1. An auxiliary optimal stopping problem.** Let  $\beta$  be a nonnegative number and  $(B_s)_{s \geq 0}$  be a standard Brownian motion with local time at  $x$  denoted by  $\tilde{L}^x$ . We denote by  $\mathcal{T}_{0,1}$  the set of all  $\sigma(B_t; t \geq 0)$ -stopping times with values in  $[0, 1]$ . Consider also a Poisson process  $(N_s)_{s \geq 0}$ , independent of  $B$ , with intensity  $\lambda$ ; we denote by  $\hat{T}_1$  its first jump time and by  $\hat{\mathcal{T}}_{0,1}$  the set of all  $\sigma((N_t, B_t); t \geq 0)$ -stopping times with values in  $[0, 1]$ . We define the functions  $v_{\lambda, \beta}$  as follows:

$$v_{\lambda, \beta}(y) = \sup_{\tau \in \hat{\mathcal{T}}_{0,1}} \mathbb{E} \left[ e^{\lambda \tau} 1_{\{N_\tau=0\}} \int_0^\tau f_{\lambda, \beta}(y + B_s) ds + \frac{\beta}{2} e^{\lambda \tau} 1_{\{N_\tau=1\}} \left( L_\tau^- (B) - L_{\hat{T}_1}^- (B) \right) \right],$$

where  $f_a(x) = x + ax^+$ . Notice that  $v_{\lambda, \beta}$  is a nonnegative function. Moreover, we have the following.

**Lemma 4.1.** *Define*

$$y_{\lambda, \beta} = -\inf\{x \in \mathbb{R} \mid v_{\lambda, \beta}(x) > 0\}.$$

We have  $0 < y_{\lambda, \beta} < 1 + \lambda\beta(2 + e^\lambda)$  and

$$\forall y < -y_{\lambda, \beta}, \quad v_{\lambda, \beta}(y) = 0.$$

We finish this subsection with an inequality, which will be used to derive a lower bound for the second derivative of  $P$  (see the proof of the upper bound in Theorem 4.7).

We define the function  $C$  on  $\mathbb{R}$  by  $C(x) = x - \lambda\beta \mathbb{E}(B_1 - x)^+$  and we have the following lemma.

**Lemma 4.2.** *For all  $x > y_{\lambda, \beta}$ , we have*

$$C(x) > 0.$$

These results will be proved in Appendix B.

**4.2. American put price expansion.** Throughout this section, we assume  $\bar{d} < 0$ , so that  $b(T) < K$ . We then have enough regularity of the American put price to derive an expansion of  $P$  around  $b(T)$  along a certain parabolic branch.

**Theorem 4.3.** *Let  $a$  be a negative number ( $a < 0$ ) and let  $b(T)$  denote the limit of  $b(t)$  when  $t$  goes to  $T$ ,  $b(T) = \lim_{t \rightarrow T} b(t)$ . If  $\bar{d} < 0$ , we have*

$$P(T - \theta, b(T)e^{a\sqrt{\theta}}) = (K - b(T)e^{a\sqrt{\theta}})^+ + C\theta^{\frac{3}{2}}v_{\lambda, \beta}\left(\frac{a}{\sigma}\right) + o(\theta^{\frac{3}{2}}),$$

where  $C = \sigma b(T)\hat{\delta}$ , with  $\lambda = \nu\{\ln \frac{K}{b(T)}\}$ ,  $\hat{\delta} = \delta + \int_{y > \ln(K/b(T))} e^y \nu(dy)$  and  $v_{\lambda, \beta}(y)$  as defined in the previous section with  $\beta = \frac{K}{b(T)\hat{\delta}}$ .

**Remark 1.** Notice that if  $\nu$  does not charge  $\ln(K/b(T))$ , meaning that  $\lambda = 0$  and  $\hat{T}_1 = \infty$  a.s., then

$$v_{\lambda, \beta}(a) = v_0(a) = \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left( \int_0^\tau (a + B_s) ds \right).$$

In this case, the American put price will have the same expansion as in the Black–Scholes model (see [9]).

The proof of Theorem 4.3 will require some estimates for the local time at  $K$  of the process  $(S_t)_{t \geq 0}$ , which we denote by  $(L_t^K)_{t \geq 0}$ . In fact, the main difference with the approach used in the Black–Scholes case lies in this analysis of the local time. The process  $L^K$  can be derived from the Ito–Tanaka formula (see [12]):

$$(4) \quad \begin{aligned} (K - S_t)^+ &= (K - S_0)^+ + \int_0^t (-1_{\{S_s \leq K\}}) S_s (\gamma_0 ds + \sigma dB_s) \\ &\quad + \sum_{0 < s \leq t} ((K - S_s)^+ - (K - S_{s-})^+) + \frac{1}{2} L_t^K. \end{aligned}$$

The following proposition provides an expansion of  $\mathbb{E}L_\tau^K$  for stopping times  $\tau$  with values in  $[0, \theta]$  with  $\theta$  close to 0.

**Proposition 4.4.** *We assume  $b(T) < K$ . Let  $a$  be a fixed negative number,  $a < 0$ , and  $S_0 = b(T)e^{a\sqrt{\theta}}$ .*

- *We have  $\limsup_{\theta \downarrow 0} \frac{\mathbb{E}(L_\theta^K)}{\theta^{3/2}} < \infty$ . Moreover, if  $\nu\{\ln(\frac{K}{b(T)})\} = 0$ ,  $\limsup_{\theta \downarrow 0} \frac{\mathbb{E}(L_\theta^K)}{\theta^{3/2}} = 0$ .*
- *If  $\nu\{\ln(K/b(T))\} \neq 0$ , then we have, for all  $\mathbb{F}$ -stopping time  $\tau$  with values in  $[0, \theta]$ ,*

$$\mathbb{E}(L_\tau^K) = 2K\mathbb{E} \left[ \left( (-a\sqrt{\theta} - \sigma B_\tau)^+ - (-a\sqrt{\theta} - \sigma B_{\hat{T}_1})^+ \right) 1_{\{\hat{T}_1 < \tau\}} \right] + o(\theta^{\frac{3}{2}}),$$

where  $\hat{T}_1 = \inf\{s \geq 0; \Delta X_s = \ln(\frac{K}{b(T)})\}$  and  $o(\theta^{3/2})$  is uniform with respect to  $\tau$ .

For the proof of Proposition 4.4, we will need an elementary estimate for the expectation of the local time of Brownian motion.

**Lemma 4.5.** *For all real number  $a$  and for all  $t > 0$ , we have*

$$0 \leq \mathbb{E}(a - B_t)^+ - a^+ \leq \sqrt{t} \frac{e^{-\frac{a^2}{2t}}}{\sqrt{2\pi}}.$$

*Proof of Lemma 4.5.* The first inequality follows from Jensen’s inequality. For the other inequality, we have

$$\begin{aligned} \mathbb{E}(a - B_t)^+ &= \int_{-\infty}^{a/\sqrt{t}} (a - \sqrt{t}y) e^{-y^2/2} \frac{dy}{\sqrt{2\pi}} \\ &= a \int_{-\infty}^{a/\sqrt{t}} e^{-y^2/2} \frac{dy}{\sqrt{2\pi}} + \sqrt{t} \frac{e^{-\frac{a^2}{2t}}}{\sqrt{2\pi}}. \end{aligned}$$

Then, if  $a \leq 0$ ,

$$\mathbb{E}(a - B_t)^+ \leq \sqrt{t} \frac{e^{-\frac{a^2}{2t}}}{\sqrt{2\pi}}.$$

If  $a \geq 0$ , we can write

$$\mathbb{E}(a - B_t)^+ - a = -a \int_{a/\sqrt{t}}^{+\infty} e^{-y^2/2} \frac{dy}{\sqrt{2\pi}} + \sqrt{t} \frac{e^{-\frac{a^2}{2t}}}{\sqrt{2\pi}} \leq \sqrt{t} \frac{e^{-\frac{a^2}{2t}}}{\sqrt{2\pi}}. \quad \blacksquare$$

Before proving Proposition 4.4, we state and prove an estimate for  $\mathbb{E}(L_\theta^K \mid S_0 = x)$ .

**Lemma 4.6.** *There exists a positive constant  $C$  such that for all  $x > 0$  and for all  $\theta > 0$ , we have*

$$\mathbb{E}(L_\theta^K \mid S_0 = x) \leq Cx \left( \sqrt{\theta} \exp\left(-\frac{(K-x)^2}{2x^2\sigma^2\theta}\right) + \theta \right).$$

*Proof of Lemma 4.6.* We will use the notation  $\mathbb{E}_x$  for  $\mathbb{E}(\cdot \mid S_0 = x)$ . Taking expectations in (4) and using the compensation formula (see, for instance, [3]), we have

$$\frac{1}{2}\mathbb{E}_x(L_\theta^K) = \mathbb{E}_x(K - S_\theta)^+ - (K - S_0)^+ + \mathbb{E}_x \left[ \int_0^\theta \left( \gamma_0 S_s 1_{\{S_s \leq K\}} - \int \Psi(S_s, y) \nu(dy) \right) ds \right],$$

where  $\Psi(x, y) = (K - xe^y)^+ - (K - x)^+$ .

We deduce easily from this equality that

$$\frac{1}{2}\mathbb{E}_x(L_\theta^K) = \mathbb{E}_x(K - S_\theta)^+ - (K - x)^+ + xO(\theta)$$

with  $O(\theta)$  independent of  $x$ . We have, with the notation  $\tilde{Z}_\theta = Z_\theta - \theta \int (e^y - 1) \nu(dy)$ ,

$$\mathbb{E}_x(K - S_\theta)^+ - (K - x)^+ = \mathbb{E}_x(K - xe^{(r-\delta-\frac{\sigma^2}{2})\theta + \sigma B_\theta + \tilde{Z}_\theta})^+ - (K - x)^+.$$

We also have

$$\begin{aligned} \mathbb{E} \left| e^{(r-\delta-\frac{\sigma^2}{2})\theta + \sigma B_\theta + \tilde{Z}_\theta} - e^{\sigma B_\theta} \right| &= e^{\sigma^2\theta/2} \mathbb{E} \left| e^{(r-\delta-\frac{\sigma^2}{2})\theta + \tilde{Z}_\theta} - 1 \right| \\ &= O(\theta). \end{aligned}$$

Therefore

$$\begin{aligned} \mathbb{E}_x(K - S_\theta)^+ - (K - x)^+ &= \mathbb{E}(K - xe^{\sigma B_\theta})^+ - (K - x)^+ + xO(\theta) \\ &= \mathbb{E}(K - x(1 + \sigma B_\theta))^+ - (K - x)^+ + xO(\theta) \\ &= x\sigma \left( \mathbb{E} \left( \frac{K-x}{x\sigma} - B_\theta \right)^+ - \left( \frac{K-x}{x\sigma} \right)^+ \right) + xO(\theta). \end{aligned}$$

Hence, using Lemma 4.5 above,

$$\mathbb{E}_x(K - S_\theta)^+ - (K - x)^+ \leq x\sigma \sqrt{\theta/(2\pi)} \exp\left(-\frac{(K-x)^2}{2x^2\sigma^2\theta}\right) + xO(\theta). \quad \blacksquare$$

*Proof of Proposition 4.4.* Let  $T_1$  be the first jump time of the process  $Z$ . We will use the following decomposition:

$$L_\theta^K = L_{\theta \wedge T_1}^K + L_\theta^K - L_{\theta \wedge T_1}^K = L_{\theta \wedge T_1}^K + 1_{\{T_1 < \theta\}} (L_\theta^K - L_{T_1}^K).$$

**Estimating  $\mathbb{E}L_{\theta \wedge T_1}^K$ .** In the stochastic interval  $[0, T_1[$ , the process  $(S_t)$  matches the process  $(\check{S}_t)$  defined by

$$\check{S}_t = S_0 e^{(\gamma_0 - \frac{\sigma^2}{2})t + \sigma B_t}.$$



We deduce (when observing that the process  $L^K$  is continuous) that

$$L_{\theta \wedge T_1}^K = \check{L}_{\theta \wedge T_1}^K \leq \check{L}_\theta^K,$$

where  $\check{L}^K$  is the local time at  $K$  of the process  $\check{S}$ . Note that

$$\frac{1}{2} \check{L}_\theta^K = (K - \check{S}_\theta)_+ - (K - S_0)_+ - \int_0^\theta (-1_{\{\check{S}_s \leq K\}}) \check{S}_s (\gamma_0 ds + \sigma dB_s).$$

As the process  $(\check{L}_\theta^K)$  increases only on  $\{\check{S}_t = K\}$ , we have

$$\check{L}_\theta^K = \check{L}_\theta^K 1_{\{\check{\tau}_K < \theta\}},$$

where  $\check{\tau}_K = \inf\{t \geq 0; \check{S}_t > K\}$ . Note that  $\check{\tau}_K = \inf\{t \geq 0; (\gamma_0 - \frac{\sigma^2}{2})t + \sigma B_t > \ln(K/S_0)\}$ , so that, with our assumptions on  $S_0$ , we have  $\mathbb{P}(\check{\tau}_K \leq \theta) = o(\theta^n)$  for all  $n > 0$ . By Hölder,

$$\mathbb{E} \check{L}_\theta^K \leq (\mathbb{P}(\check{\tau}_K < \theta))^{1-\frac{1}{p}} \|\check{L}_\theta^K\|_p, \quad p > 1.$$

We easily deduce that  $\mathbb{E} \check{L}_\theta^K = o(\theta^n)$  for all  $n > 0$ , so that  $\mathbb{E} L_{\theta \wedge T_1}^K = o(\theta^n)$  for all  $n > 0$ .

**Estimating  $\mathbb{E} [1_{\{T_1 < \theta\}} (L_\theta^K - L_{T_1}^K)]$ .** By the strong Markov property, we have

$$\begin{aligned} \mathbb{E} [1_{\{T_1 < \theta\}} (L_\theta^K - L_{T_1}^K)] &\leq \mathbb{E} [1_{\{T_1 < \theta\}} (L_{T_1+\theta}^K - L_{T_1}^K)] \\ (5) \qquad \qquad \qquad &= \mathbb{E} \left( 1_{\{T_1 < \theta\}} \mathbb{E}_{S_{T_1}}(L_\theta^K) \right), \end{aligned}$$

where  $\mathbb{E}_x$  is the expectation associated to  $\mathbb{P}_x$  and  $\mathbb{P}_x$  defines the law of  $S_t$  when  $S_0 = x$ .

Using Lemma 4.6, we deduce

$$(6) \quad \mathbb{E} [1_{\{T_1 < \theta\}} (L_{T_1+\theta}^K - L_{T_1}^K)] \leq C \mathbb{E} \left( 1_{\{T_1 < \theta\}} S_{T_1} \left( \sqrt{\theta} \exp \left( -\frac{(K - S_{T_1})^2}{2S_{T_1}^2 \sigma^2 \theta} \right) + \theta \right) \right).$$

At this stage, we notice that  $\mathbb{P}(T_1 \leq \theta) = O(\theta)$  and that, conditionally on  $\{T_1 \leq \theta\}$ ,  $T_1$  is uniformly distributed on  $[0, \theta]$ .

As  $Z_{T_1}$  is independent of both  $T_1$  and  $B$ , we see that, conditionally to  $\{T_1 < \theta\}$ ,  $S_{T_1}$  has the same law as the random variable  $\zeta_\theta$  defined by

$$\zeta_\theta = K \exp \left\{ (V - \ln(K/b(T))) + \sqrt{\theta} \left( a + \left( \gamma_0 - \frac{\sigma^2}{2} \right) \sqrt{\theta} U + \sigma g \sqrt{U} \right) \right\},$$

where  $U$ ,  $g$ , and  $V$  are independent random variables,  $U$  is uniform on  $[0, 1]$ ,  $g$  is standard Gaussian, and  $V$  has the same law as  $Z_{T_1}$ . Therefore, the estimate (6) can be rewritten as follows:

$$(7) \quad \mathbb{E} [1_{\{T_1 < \theta\}} (L_{T_1+\theta}^K - L_{T_1}^K)] \leq C \sqrt{\theta} \mathbb{P}(T_1 < \theta) \mathbb{E} \left( \zeta_\theta \left( \exp \left( -\frac{(K - \zeta_\theta)^2}{2\zeta_\theta^2 \sigma^2 \theta} \right) + \sqrt{\theta} \right) \right)$$

$$(8) \qquad \qquad \qquad \leq C \sqrt{\theta} \mathbb{P}(T_1 < \theta) \mathbb{E} \left( \zeta_\theta \left( 1 + \sqrt{\theta} \right) \right).$$

Clearly, with probability one,

$$\lim_{\theta \rightarrow 0} \zeta_\theta = K \exp \left( V - \ln \left( \frac{K}{b(T)} \right) \right),$$

and we easily deduce from (8) that  $\mathbb{E} [1_{\{T_1 < \theta\}} (L_{T_1+\theta}^K - L_{T_1}^K)] = O(\theta^{3/2})$ . We can now conclude that  $\mathbb{E}(L_\theta^K) = O(\theta^{3/2})$ .

Moreover, if we assume  $\nu\{\ln(\frac{K}{b(T)})\} = 0$ , we have  $V - \ln(\frac{K}{b(T)}) \neq 0$  a.s., so that  $\lim_{\theta \rightarrow 0} \zeta_\theta \neq K$  a.s. and, by dominated convergence,

$$\lim_{\theta \downarrow 0} \mathbb{E} \left( \zeta_\theta \exp \left( -\frac{(K - \zeta_\theta)^2}{2\zeta_\theta^2 \sigma^2 \theta} \right) \right) = 0.$$

Therefore, using (7),  $\mathbb{E} [1_{\{T_1 < \theta\}} (L_{T_1+\theta}^K - L_{T_1}^K)] = o(\theta^{3/2})$ , hence

$$\mathbb{E} \left( L_\theta^K \mid S_0 = b(T)e^{a\sqrt{\theta}} \right) = o(\theta^{3/2}).$$

**Expansion of  $\mathbb{E}(L_\tau^K)$ , in the case where  $\nu\{\ln(\frac{K}{b(T)})\} > 0$ .** For the proof of the second part of the proposition, we assume  $\nu\{\ln(\frac{K}{b(T)})\} > 0$ , and we introduce the processes  $\hat{X}$  and  $\hat{Z}$  such that

$$\hat{Z}_t = \sum_{s < t} \Delta \tilde{X}_s 1_{\{\Delta \tilde{X}_s = \ln \frac{K}{b(T)}\}} \quad \text{and} \quad \hat{X} = \tilde{X} - \hat{Z},$$

and  $\hat{T}_1 = \inf\{s \geq 0, \hat{Z}_t \neq 0\}$ .

For any stopping time with values in  $[0, \theta]$ , we have

$$\begin{aligned} \mathbb{E}(L_\tau^K) &= \mathbb{E}(L_{\tau \wedge T_1}^K) + \mathbb{E}(L_\tau^K - L_{\tau \wedge T_1}^K) \\ &= \mathbb{E}(L_\tau^K - L_{\tau \wedge T_1}^K) + o(\theta^{3/2}), \end{aligned}$$

where we have used the inequality  $\mathbb{E}(L_{\tau \wedge T_1}^K) \leq \mathbb{E}(L_{\theta \wedge T_1}^K)$  and the fact (observed in the first step of the proof) that  $\mathbb{E}(L_{\theta \wedge T_1}^K) = o(\theta^{3/2})$ .

We now observe that since  $T_1 \leq \hat{T}_1$  and  $\tau \leq \theta$ ,

$$0 \leq \mathbb{E} \left( L_{\tau \wedge \hat{T}_1}^K - L_{\tau \wedge T_1}^K \right) \leq \mathbb{E} \left( L_{\theta \wedge \hat{T}_1}^K \right).$$

On the stochastic interval  $[0, \hat{T}_1)$ , the process  $\tilde{X}$  matches the process  $\hat{X}$  whose Lévy measure does not charge the point  $\ln(K/b(T))$ . So, we have  $\mathbb{E}(L_{\theta \wedge \hat{T}_1}^K) = \mathbb{E}(\hat{L}_{\theta \wedge \hat{T}_1}^K) \leq \mathbb{E}(\hat{L}_\theta^K)$ , where  $\hat{L}^K$  is the local time at  $K$  of the process  $S$  obtained by replacing  $\tilde{X}$  with  $\hat{X}$  in the definition of  $S$ . Since the Lévy measure of  $\hat{X}$  does not charge  $\ln(K/b(T))$ , we deduce from the above discussion that  $\mathbb{E}(\hat{L}_\theta^K) = o(\theta^{3/2})$ . Hence

$$\mathbb{E}(L_\tau^K) = \mathbb{E} \left( L_\tau^K - L_{\tau \wedge \hat{T}_1}^K \right) + o(\theta^{3/2}).$$

Going back to (4) and using again the compensation formula, we have

$$\begin{aligned} \frac{1}{2}\mathbb{E}\left(L_{\tau}^K - L_{\tau\wedge\hat{T}_1}^K\right) &= \mathbb{E}\left((K - S_{\tau})^+ - (K - S_{\tau\wedge\hat{T}_1})^+\right) \\ &\quad + \mathbb{E}\left[\int_{\tau\wedge\hat{T}_1}^{\tau}\left(\gamma_0 S_s 1_{\{S_s \leq K\}} - \int \Psi(S_s, y)\nu(dy)\right) ds\right] \end{aligned}$$

with  $\Psi(x, y) = (K - xe^y)^+ - (K - x)^+$ . Note that

$$\left|\mathbb{E}\left[\int_{\tau\wedge\hat{T}_1}^{\tau}\left(\gamma_0 S_s 1_{\{S_s \leq K\}} - \int \Psi(S_s, y)\nu(dy)\right) ds\right]\right| \leq \mathbb{E}\left(1_{\{\hat{T}_1 < \theta\}} \int_0^{\theta} j(S_s) ds\right)$$

with  $j(z) = |\gamma_0|z + \int |\Psi(z, y)|\nu(dy)$ . Since the function  $\Psi$  is bounded, we easily derive  $\mathbb{E}(1_{\{\hat{T}_1 < \theta\}} \int_0^{\theta} j(S_s) ds) = O(\theta^2)$ , so that

$$\begin{aligned} \frac{1}{2}\mathbb{E}\left(L_{\tau}^K - L_{\tau\wedge\hat{T}_1}^K\right) &= \mathbb{E}\left((K - S_{\tau})^+ - (K - S_{\tau\wedge\hat{T}_1})^+\right) + O(\theta^2) \\ &= \mathbb{E}\left[1_{\{\hat{T}_1 < \tau\}}\left((K - S_{\tau})^+ - (K - S_{\hat{T}_1})^+\right)\right] + O(\theta^2). \end{aligned}$$

We now argue that up to  $O(\theta^2)$ , we have at most one jump before  $\theta$ . More precisely, let  $(N_t)_{t \geq 0}$  be the counting process of the jumps of  $Z$ , so that

$$N_{\theta} = \sum_{0 < s \leq \theta} 1_{\{\Delta \hat{X}_s \neq 0\}} = \sum_{s \leq \theta} 1_{\{\Delta Z_s \neq 0\}}.$$

We have  $\mathbb{P}(N_{\theta} \geq 2) = O(\theta^2)$ , so that

$$\begin{aligned} &\mathbb{E}\left[1_{\{\hat{T}_1 < \tau\}}\left((K - S_{\tau})^+ - (K - S_{\hat{T}_1})^+\right)\right] \\ &= \mathbb{E}\left[1_{\{\hat{T}_1 < \tau, N_{\theta} \leq 1\}}\left((K - S_{\tau})^+ - (K - S_{\hat{T}_1})^+\right)\right] + O(\theta^2). \end{aligned}$$

On  $\{\hat{T}_1 < \tau, N_{\theta} \leq 1\}$ , we have, for  $\hat{T}_1 \leq s \leq \theta$ ,

$$S_s = S_0 e^{\hat{X}_s + \hat{Z}_{\hat{T}_1}} = S_0 e^{\hat{X}_s} K/b(T) = K e^{a\sqrt{\theta} + \hat{X}_s} = K e^{a\sqrt{\theta} + \mu s + \sigma B_s},$$

where  $\mu = \gamma_0 - \frac{\sigma^2}{2}$ . Therefore

$$\begin{aligned} \frac{1}{2}\mathbb{E}\left(L_{\tau}^K - L_{\tau\wedge\hat{T}_1}^K\right) &= K\mathbb{E}\left[1_{\{\hat{T}_1 < \tau\}}\left((1 - e^{a\sqrt{\theta} + \mu\tau + \sigma B_{\tau}})^+ - (1 - e^{a\sqrt{\theta} + \mu\hat{T}_1 + \sigma B_{\hat{T}_1}})^+\right)\right] + O(\theta^2) \\ &= K\mathbb{E}\left[\left((-a\sqrt{\theta} - \mu\tau - \sigma B_{\tau})^+ - (-a\sqrt{\theta} - \mu\hat{T}_1 - \sigma B_{\hat{T}_1})^+\right) 1_{\{\hat{T}_1 < \tau\}}\right] + O(\theta^2) \\ &= K\mathbb{E}\left[\left((-a\sqrt{\theta} - \sigma B_{\tau})^+ - (-a\sqrt{\theta} - \sigma B_{\hat{T}_1})^+\right) 1_{\{\hat{T}_1 < \tau\}}\right] + O(\theta^2). \end{aligned}$$

The last two equalities follow from  $\mathbb{P}(\hat{T}_1 < \tau) = O(\theta)$ ,  $|(1 - e^x + x)1_{\{x \leq 0\}}| \leq \frac{x^2}{2}$ , and the fact that  $\mathbb{E}(B_{\tau})^2 \leq \theta$ . ■

*Proof of Theorem 4.3.* First of all, we recall our notation  $\check{X}_t = \tilde{X}_t - Z_t$ ,  $\check{S}_t = \tilde{S}_t/e^{Z_t}$ , and  $T_1$  the first jump time  $T_1 = \inf\{t > 0 | Z_t \neq 0\}$ , and from now on we consider  $S_0$  as a function of  $\theta$ . More precisely, we denote by  $S_0^\theta = b(T)e^{a\sqrt{\theta}} = e^{x_0+a\sqrt{\theta}}$  with  $a < 0$  and  $x_0 = \ln(b(T))$ .

We deduce from (4) and the compensation formula that for all stopping times  $\tau \in \mathcal{T}_{0,\theta}$ ,

$$\begin{aligned} & \mathbb{E} [e^{-r\tau}(K - S_\tau)^+] - (K - S_0)^+ \\ &= \mathbb{E} \left[ \int_0^\tau \left( e^{-rs} 1_{\{S_s \leq K\}} \left( -rK + \delta S_s + S_s \int (e^y - 1)\nu(dy) \right) \right. \right. \\ & \quad \left. \left. + e^{-rs} \int [(K - S_s e^y)^+ - (K - S_s)^+] \nu(dy) \right) ds \right] + \frac{1}{2} \mathbb{E} \left( \int_0^\tau e^{-rs} dL_s^K \right) \\ (9) \quad &= \mathcal{I}^a(\tau) + \mathcal{J}^a(\tau), \end{aligned}$$

where, with the notation  $\Psi(x, y) = (K - xe^y)^+ - (K - x)^+$ ,

$$\begin{aligned} \mathcal{I}^a(\tau) = \mathbb{E} \left[ \int_0^\tau \left( e^{-rs} 1_{\{S_s \leq K\}} \left( -rK + \delta S_s + S_s \int (e^y - 1)\nu(dy) \right) \right. \right. \\ \left. \left. + e^{-rs} \int \Psi(S_s, y)\nu(dy) \right) ds \right] \end{aligned}$$

and

$$\mathcal{J}^a(\tau) = \frac{1}{2} \mathbb{E} \left( \int_0^\tau e^{-rs} dL_s^K \right).$$

Note that since  $\tau \leq \theta$ ,  $\mathbb{E} \left( \int_0^\tau (1 - e^{-rs}) dL_s^K \right) \leq r\theta \mathbb{E}(L_\theta^K)$ , so that using Proposition 4.4,

$$\begin{aligned} \mathcal{J}^a(\tau) &= \frac{1}{2} \mathbb{E}(L_\tau^K) + O(\theta^{1+\frac{3}{2}}) \\ (10) \quad &= K\mathbb{E} \left[ \left( (-a\sqrt{\theta} - \sigma B_\tau)^+ - (-a\sqrt{\theta} - \sigma B_{\hat{T}_1})^+ \right) 1_{\{\hat{T}_1 < \tau\}} \right] + o(\theta^{\frac{3}{2}}). \end{aligned}$$

**Estimating  $\mathcal{I}^a$ .** First of all, note that we have

$$\begin{aligned} & \mathbb{E} \left[ \int_0^\tau \left( e^{-rs} 1_{\{S_s > K\}} \int |(K - S_s e^y)^+ - (K - S_s)^+| \nu(dy) \right) ds \right] \\ & \leq K\nu(\mathbb{R}) \int_0^\theta \mathbb{P}\{S_s > K\} ds \\ & \leq K\nu(\mathbb{R}) \int_0^\theta \mathbb{P}\{S_s > K, T_1 > \theta\} + \mathbb{P}\{S_s > K, T_1 \leq \theta\} ds \\ & \leq K\nu(\mathbb{R}) \left( \int_0^\theta \mathbb{P}\{\check{S}_s > K\} ds + \theta \mathbb{P}\{T_1 \leq \theta\} \right) = O(\theta^2). \end{aligned}$$

Here, we have used the fact that with the notation  $\check{\tau}_K = \inf\{t \geq 0; \check{S}_t > K\}$ ,  $\mathbb{P}(\check{S}_s > K) = \mathbb{P}(\check{\tau}_K \leq s) \leq \mathbb{P}(\check{\tau}_K \leq \theta) = o(\theta^n)$  for all  $n > 0$ , as observed in the proof of Proposition 4.4.

We can now write

$$\begin{aligned} \mathcal{I}^a(\tau) &= \mathbb{E} \left[ \int_0^\tau e^{-rs} 1_{\{S_s \leq K\}} \left( -rK + \delta S_s + \int (S_s(e^y - 1) + \Psi(S_s, y)) \nu(dy) \right) ds \right] + O(\theta^2) \\ &= \mathbb{E} \left( \int_0^\tau e^{-rs} 1_{\{S_s \leq K\}} \left( -rK + \delta S_s + \int (S_s e^y - K)^+ \nu(dy) \right) ds \right) + O(\theta^2), \end{aligned}$$

where the last equality follows from

$$1_{\{x \leq K\}} (x(e^y - 1) + [(K - xe^y)^+ - (K - x)^+]) = (xe^y - K)^+ 1_{\{x \leq K\}}.$$

We can also omit  $e^{-rs}$  in the expression as an error of the order of  $O(\theta^2)$ . Then we obtain, for all stopping times  $\tau$  with values in  $[0, \theta]$ ,

$$\mathcal{I}^a(\tau) = \mathbb{E} \left( \int_0^\tau 1_{\{S_s \leq K\}} \left( -rK + \delta S_s + \int (S_s e^y - K)^+ \nu(dy) \right) ds \right) + O(\theta^2).$$

We denote

$$h(x) = -rK + \delta e^x + \int (e^x e^y - K)^+ \nu(dy)$$

and recall that  $S_t = S_0^\theta e^{\tilde{X}_t} = b(T) e^{a\sqrt{\theta} + \tilde{X}_t} = b(T) e^{\tilde{X}_t^{a\sqrt{\theta}}} = e^{x_0 + \tilde{X}_t^{a\sqrt{\theta}}}$ , where  $\tilde{X}_t^y = y + \tilde{X}_t$ . We thus have

$$(11) \quad \mathcal{I}^a(\tau) = \mathbb{E} \left( \underbrace{\int_0^\tau 1_{\{a\sqrt{\theta} + \tilde{X}_s \leq \ln \frac{K}{b(T)}\}} h(x_0 + a\sqrt{\theta} + \tilde{X}_s) ds}_{(I)} \right) + o(\theta^{\frac{3}{2}}).$$

Now, we will try to express the quantity (I) under a more appropriate form. The first step is to neglect the contribution of the finite variation part of the process  $\tilde{X}$ . Notice that

$$|1_{\{x \leq \ln(K)\}} h(x)| \leq K(r \vee |\bar{d}|) \quad \text{and} \quad |h(x) - h(y)| \leq |e^x - e^y| \left( \delta + \int e^y \nu(dy) \right).$$

Moreover, for all  $(x, y) \in \mathbb{R}^2$ , we have

$$\begin{aligned} & |1_{\{x \leq \ln(K)\}} h(x) - 1_{\{y \leq \ln(K)\}} h(y)| \\ &= |(h(x) - h(y)) 1_{\{x \vee y \leq \ln(K)\}} + h(x) 1_{\{x \leq \ln(K) < y\}} - h(y) 1_{\{y \leq \ln(K) < x\}}| \\ &\leq A_0 |e^x - e^y| 1_{\{x \vee y \leq \ln(K)\}} + A_1 (1_{\{\ln(K) < y\}} + 1_{\{\ln(K) < x\}}), \end{aligned}$$

where  $A_1 = K(r \vee |\bar{d}|)$  and  $A_0 = \delta + \int e^y \nu(du)$ . Let  $k_b = \ln(\frac{K}{b(T)}) > 0$  and recall that  $\tilde{X}_t - \sigma B_t = (\gamma_0 - \frac{\sigma^2}{2})t + Z_t$ ; then

$$\begin{aligned} & \left| 1_{\{x_0 + a\sqrt{\theta} + \tilde{X}_s \leq \ln K\}} h(x_0 + a\sqrt{\theta} + \tilde{X}_s) - 1_{\{x_0 + a\sqrt{\theta} + \sigma B_s \leq \ln K\}} h(x_0 + a\sqrt{\theta} + \sigma B_s) \right| \\ &\leq A_0 \left| e^{x_0 + a\sqrt{\theta} + \tilde{X}_s} - e^{x_0 + a\sqrt{\theta} + \sigma B_s} \right| 1_{\{\tilde{X}_s \vee \sigma B_s \leq k_b - a\sqrt{\theta}\}} + A_1 (1_{\{k_b - a\sqrt{\theta} < \sigma B_s\}} + 1_{\{k_b - a\sqrt{\theta} < \tilde{X}_s\}}) \\ &\leq A_0 b(T) e^{\sigma B_s} \left| e^{(\gamma_0 - \frac{\sigma^2}{2})s + Z_s} - 1 \right| + A_1 (1_{\{k_b < \sigma B_s\}} + 1_{\{k_b < \tilde{X}_s\}}), \end{aligned}$$

where the last inequality is due to  $a < 0$  and  $e^{x_0} = b(T)$ .

Note that for all  $s \in [0, \theta]$ ,

$$\mathbb{P}(k_b < \sigma B_s) \leq \mathbb{P} \left( \frac{k_b}{\sigma\sqrt{\theta}} < B_1 \right) \leq C\sqrt{\theta} e^{-\frac{k_b^2}{2\sigma^2\theta}}.$$

Moreover, for  $\theta$  small enough, we have  $\frac{k_b}{2} < k_b - (\gamma_0 - \frac{\sigma^2}{2})s$ , so that

$$\mathbb{P}(k_b < \tilde{X}_s) \leq \mathbb{P}\left(\frac{k_b - (\gamma_0 - \frac{\sigma^2}{2})s}{\sigma\sqrt{\theta}} < B_1\right) + \mathbb{P}(T_1 \leq \theta) \leq C\sqrt{\theta}e^{-\frac{k_b^2}{8\sigma^2\theta}} + A\theta$$

and

$$\mathbb{E}\left(e^{\sigma B_s} \left| e^{(\gamma_0 - \frac{\sigma^2}{2})s + Z_s} - 1 \right|\right) \leq e^{\frac{\sigma^2}{2}s} \left| e^{(r - \delta - \frac{\sigma^2}{2})s} - 1 \right| + e^{\frac{\sigma^2}{2}s} \mathbb{E}\left| e^{Z_s - s \int (e^y - 1)\nu(dy)} - 1 \right| \leq D\theta.$$

Hence,

$$\int_0^\theta \mathbb{E}\left(\left| 1_{\{x_0 + a\sqrt{\theta} + \tilde{X}_s \leq \ln K\}} h(x_0 + a\sqrt{\theta} + \tilde{X}_s) - 1_{\{x_0 + a\sqrt{\theta} + \sigma B_s \leq \ln K\}} h(x_0 + a\sqrt{\theta} + \sigma B_s) \right|\right) ds = O(\theta^2).$$

Thanks to this estimation, (11) becomes

$$(12) \quad \mathcal{I}^a(\tau) = \mathbb{E}\left(\int_0^\tau 1_{\{\xi_s^{a,\theta} \leq \ln \frac{K}{b(T)}\}} h(x_0 + \xi_s^{a,\theta}) ds\right) + o(\theta^{\frac{3}{2}}),$$

where

$$\xi_s^{a,\theta} = a\sqrt{\theta} + \sigma B_s.$$

We will now use an expansion of  $h$  around  $x_0$ . When  $h$  is differentiable at  $x_0$ , we have  $h(x_0 + y) = h(x_0) + yh'(x_0) + o(y)$ . As we will see, when  $\nu\{\ln(K/b(T))\} >$ , there is a jump in the derivative that modifies the expansion.

The function  $h$  is convex; therefore it has right-hand and left-hand derivatives everywhere. Particularly, we have, for  $x < \ln(K)$ ,

$$h'_g(x) = e^x \left( \delta + \int e^y 1_{\{y > \ln(K) - x\}} \nu(dy) \right)$$

and

$$h'_d(x) = e^x \left( \delta + \int e^y 1_{\{y \geq \ln(K) - x\}} \nu(dy) \right).$$

Hence, we can write

$$h'_d(x_0)(x - x_0)^+ - h'_g(x_0)(x - x_0)^- \leq h(x) - h(x_0) \leq h'_g(x)(x - x_0)^+ - h'_d(x)(x - x_0)^-,$$

and hence

$$\begin{aligned} 0 &\leq h(x) - (h(x_0) + h'_d(x_0)(x - x_0)^+ - h'_g(x_0)(x - x_0)^-) \\ &\leq (h'_g(x) - h'_d(x_0))(x - x_0)^+ + (h'_g(x_0) - h'_d(x))(x - x_0)^- \\ &= (h'_g(x \vee x_0) - h'_d(x \wedge x_0)) |x - x_0|. \end{aligned}$$

Thanks to the equation characterizing  $b(T)$  when  $\bar{d} < 0$ , we have  $h(x_0) = h(\ln(b(T))) = 0$ . We thus obtain, by setting  $\Delta h'(x_0) = h'_d(x_0) - h'_g(x_0)$ ,

$$h(x_0 + x) = \Delta h'(x_0)x^+ + h'_g(x_0)x + |x| \tilde{R}(x),$$

where  $\tilde{R}(x) \xrightarrow{x \rightarrow 0} 0$ , and

$$\begin{aligned} 0 \leq \tilde{R}(x) &\leq (h'_g(x_0 + x^+) - h'_d(x_0 - x^-)) \\ &\leq L(1 + e^x), \end{aligned}$$

with  $L$  a positive constant. We can then write

$$\begin{aligned} &1_{\{\xi_s^{a,\theta} \leq \ln \frac{K}{b(T)}\}} h(x_0 + \xi_s^{a,\theta}) \\ &= \left( \Delta h'(x_0)(\xi_s^{a,\theta})^+ + h'_g(x_0)\xi_s^{a,\theta} \right) \left( 1 - 1_{\{\xi_s^{a,\theta} > \ln \frac{K}{b(T)}\}} \right) \\ (13) \quad &+ \left| \xi_s^{a,\theta} \right| \tilde{R}(\xi_s^{a,\theta}) 1_{\{\xi_s^{a,\theta} \leq \ln \frac{K}{b(T)}\}}. \end{aligned}$$

We claim that

$$(14) \quad \mathbb{E} \int_0^\theta \left| \xi_s^{a,\theta} \right| \tilde{R}(\xi_s^{a,\theta}) 1_{\{\xi_s^{a,\theta} \leq \ln \frac{K}{b(T)}\}} ds = o(\theta^{\frac{3}{2}})$$

and

$$(15) \quad \mathbb{E} \int_0^\theta \left| \Delta h'(x_0)(\xi_s^{a,\theta})^+ + h'_g(x_0)\xi_s^{a,\theta} \right| 1_{\{\xi_s^{a,\theta} > \ln \frac{K}{b(T)}\}} ds = o(\theta^{\frac{3}{2}}).$$

Indeed, for (14), we have, by setting  $s = u\theta$  and using the fact that  $\xi_{\theta u}^{a,\theta}$  has the same distribution as  $\sqrt{\theta}\xi_u^{a,1}$ ,

$$\begin{aligned} &\left| \mathbb{E} \left( \int_0^\theta \left| \xi_s^{a,\theta} \right| \tilde{R}(\xi_s^{a,\theta}) 1_{\{\xi_s^{a,\theta} \leq \ln \frac{K}{b(T)}\}} ds \right) \right| \\ &= \theta^{\frac{3}{2}} \int_0^1 \mathbb{E} \left[ \left| \xi_u^{a,1} \right| \tilde{R}(\sqrt{\theta}\xi_u^{a,1}) 1_{\{\sqrt{\theta}\xi_u^{a,1} \leq \ln \frac{K}{b(T)}\}} \right] du. \end{aligned}$$

As  $|\tilde{R}(x)| \leq L(e^x + 1)$  and  $|\tilde{R}(x)| \xrightarrow{x \rightarrow 0} 0$ , we have by dominated convergence

$$\lim_{\theta \downarrow 0} \left( \int_0^1 \mathbb{E} \left[ \left| \xi_u^{a,1} \right| \tilde{R}(\sqrt{\theta}\xi_u^{a,1}) \right] du \right) = 0.$$

This proves (14). For (15), we have, for some positive constant  $C$ ,

$$\begin{aligned} &\mathbb{E} \int_0^\theta \left| \Delta h'(x_0)(\xi_s^{a,\theta})^+ + h'_g(x_0)\xi_s^{a,\theta} \right| 1_{\{\xi_s^{a,\theta} > \ln \frac{K}{b(T)}\}} ds \\ &\leq C\sqrt{\theta} \int_0^\theta \mathbb{E} \left[ \left( |a| + \sigma \sqrt{\frac{s}{\theta}} |B_1| \right) 1_{\{a + \sigma \sqrt{s/\theta} B_1 > \frac{1}{\sqrt{\theta}} \ln \frac{K}{b(T)}\}} \right] ds \\ &\leq C\theta^{\frac{3}{2}} \sqrt{\mathbb{E}(|a| + |B_1|)^2} \sqrt{\mathbb{P} \left\{ a + \sigma B_1 > \frac{1}{\sqrt{\theta}} \ln \frac{K}{b(T)} \right\}} \\ &= O(\theta^n). \end{aligned}$$

Going back to (13), we deduce from (14) and (15)

$$(16) \quad \begin{aligned} \mathcal{I}^a(\tau) &= h'_g(x_0) \mathbb{E} \int_0^\tau \xi_s^{a,\theta} ds + \Delta h'(x_0) \mathbb{E} \int_0^\tau (\xi_s^{a,\theta})^+ ds + o(\theta^{\frac{3}{2}}), \\ &= b(T) \hat{\delta} \mathbb{E} \left( \int_0^\tau (a\sqrt{\theta} + \sigma B_s) + \lambda \beta (a\sqrt{\theta} + \sigma B_s)^+ ds \right) + o(\theta^{\frac{3}{2}}) \end{aligned}$$

with  $\hat{\delta} = \delta + \int_{y > \ln \frac{K}{b(T)}} e^y \nu(dy)$ ,  $\beta = \frac{K}{b(T)\hat{\delta}}$ ,  $\lambda = \nu\{\ln \frac{K}{b(T)}\}$  and we recall that  $h'_g(x_0) = b(T)\hat{\delta}$  and  $\Delta h'(x_0) = K\nu\{\ln \frac{K}{b(T)}\}$ , so that  $\lambda\beta = \frac{\Delta h'(x_0)}{h'_g(x_0)}$ .

Going back to (9) and using (10) and (16), we obtain

$$\begin{aligned} \mathbb{E}(e^{-r\tau}(K - S_\tau)^+) &= (K - S_0)^+ + \mathbb{E} \left( b(T) \hat{\delta} \int_0^\tau (a\sqrt{\theta} + \sigma B_s + \lambda\beta(a\sqrt{\theta} + \sigma B_s)^+) ds \right) \\ &\quad + K 1_{\{\hat{T}_1 < \tau\}} \left( (a\sqrt{\theta} + \sigma B_\tau)^+ - (a\sqrt{\theta} + \sigma B_{\hat{T}_1})^+ \right) + o(\theta^{3/2}) \end{aligned}$$

with  $o(\theta^{3/2})$  uniform with respect to  $\tau$ . Hence

$$P(T - \theta, b(T)e^{a\sqrt{\theta}}) = (K - b(T)e^{a\sqrt{\theta}})^+ + \sigma b(T) \hat{\delta} \bar{v}_{\lambda,\beta,\theta}(a/\sigma) + o(\theta^{3/2}),$$

where  $\bar{v}_{\lambda,\beta,\theta}$  is defined by

$$\bar{v}_{\lambda,\beta,\theta}(y) = \sup_{\tau \in \mathcal{T}_{0,\theta}} \mathbb{E} \left( \int_0^\tau f_{\lambda\beta}(y\sqrt{\theta} + B_s) ds + \beta 1_{\{\hat{T}_1 < \tau\}} \left( (y\sqrt{\theta} + B_\tau)^+ - (y\sqrt{\theta} + B_{\hat{T}_1})^+ \right) \right)$$

with  $f_a(x) = x + ax^+$ . Recall that  $\beta = K/(b(T)\hat{\delta})$ . To simplify the expression of  $\bar{v}_{\lambda,\beta,\theta}$ , we notice first that if we set  $B_t^\theta = B_{\theta t}/\sqrt{\theta}$ , we can write

$$\begin{aligned} \bar{v}_{\lambda,\beta,\theta} &= \sqrt{\theta} \sup_{\tau \in \mathcal{T}_{0,\theta}} \mathbb{E} \left( \int_0^\tau f_{\lambda\beta}(y + B_{s/\theta}^\theta) ds + \beta 1_{\{\hat{T}_1 < \tau\}} \left( (y + B_{\tau/\theta}^\theta)^+ - (y + B_{\hat{T}_1/\theta}^\theta)^+ \right) \right) \\ &= \sqrt{\theta} \sup_{\tau \in \mathcal{T}_{0,\theta}} \mathbb{E} \left( \theta \int_0^{\tau/\theta} f_{\lambda\beta}(y + B_s^\theta) ds + \beta 1_{\{\hat{T}_1 < \tau\}} \left( (y + B_{\tau/\theta}^\theta)^+ - (y + B_{\hat{T}_1/\theta}^\theta)^+ \right) \right). \end{aligned}$$

We also notice that  $\tau \in \mathcal{T}_{0,\theta}$  if and only if  $\tau/\theta \in \mathcal{T}_{0,1}^\theta$ , where  $\mathcal{T}_{0,1}^\theta$  is the set of the stopping times of the filtration  $(\mathcal{F}_{\theta t})_{t \geq 0}$ , with values in  $[0, 1]$ , so that

$$\bar{v}_{\lambda,\beta,\theta} = \sqrt{\theta} \sup_{\tau \in \mathcal{T}_{0,1}^\theta} \mathbb{E} \left( \theta \int_0^\tau f_{\lambda\beta}(y + B_s^\theta) ds + \beta 1_{\{\hat{T}_1 < \theta\tau\}} \left( (y + B_{\tau}^\theta)^+ - (y + B_{\hat{T}_1/\theta}^\theta)^+ \right) \right).$$

Note that  $\bar{v}_{\lambda,\beta,\theta}(y)$  does not change if we replace  $\mathcal{T}_{0,1}^\theta$  by  $\hat{\mathcal{T}}_{0,1}$  the set of the stopping times of the natural filtration of the couple  $(B_t^\theta, \hat{N}_{\theta t})$ , where  $\hat{N}$  is defined by

$$\hat{N}_t = \sum_{0 < s \leq t} 1_{\{\Delta Z_s = \ln(K/b(T))\}}.$$



The process  $(\hat{N}_{\theta t})_{t \geq 0}$  is a Poisson process with intensity  $\theta\lambda$ , where  $\lambda = \nu\{\ln(K/b(T))\}$ . Under the probability  $\hat{\mathbb{P}}$ , defined by

$$\frac{d\hat{\mathbb{P}}}{d\mathbb{P}} = \theta^{\hat{N}_1} e^{-\lambda(\theta-1)},$$

the process  $(B_t, \hat{N}_t)_{0 \leq t \leq 1}$  has the same law as  $(B_t^\theta, \hat{N}_{\theta t})_{0 \leq t \leq 1}$ . Observe that  $(\theta^{\hat{N}_t} e^{-\lambda t(\theta-1)})_{t \geq 0}$  is a martingale. Hence,

$$\begin{aligned} \bar{v}_{\lambda, \beta, \theta}(y) &= \sqrt{\theta} \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left[ \theta^{\hat{N}_1} e^{-\lambda(\theta-1)} \left( \theta \int_0^\tau f_{\lambda\beta}(y + B_s) ds + \beta 1_{\{\hat{T}_1 < \tau\}} \right. \right. \\ &\quad \left. \left. \times \cdot \left( (y + B_\tau)^+ - (y + B_{\hat{T}_1})^+ \right) \right) \right] \\ &= \sqrt{\theta} \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left[ \theta^{\hat{N}_\tau} e^{-\lambda\tau(\theta-1)} \left( \theta \int_0^\tau f_{\lambda\beta}(y + B_s) ds + \frac{\beta}{2} 1_{\{\hat{T}_1 < \tau\}} \left( L_\tau^{-y}(B) - L_{\hat{T}_1}^{-y}(B) \right) \right) \right], \end{aligned}$$

where  $L^{-y}(B)$  denotes the local time of  $B$  at  $-y$ . We have for  $\tau \in \mathcal{T}_{0,1}$ ,

$$\mathbb{E} \left[ \theta^{\hat{N}_\tau} e^{-\lambda\tau(\theta-1)} \left( \theta \int_0^\tau f_{\lambda\beta}(y + B_s) ds \right) \right] = \theta \mathbb{E} \left[ 1_{\{\hat{N}_\tau=0\}} e^{-\lambda\tau(\theta-1)} \left( \int_0^\tau f_{\lambda\beta}(y + B_s) ds \right) \right] + \theta R_\tau,$$

and if  $\theta \leq 1$

$$|R_\tau| \leq \theta \mathbb{E} \left[ 1_{\{\hat{N}_\tau \geq 1\}} e^{-\lambda\tau(\theta-1)} \left( \int_0^\tau |f_{\lambda\beta}(y + B_s)| ds \right) \right] = O(\theta).$$

Hence,

$$\mathbb{E} \left[ \theta^{\hat{N}_\tau} e^{-\lambda\tau(\theta-1)} \left( \theta \int_0^\tau f_{\lambda\beta}(y + B_s) ds \right) \right] = \theta \mathbb{E} \left[ 1_{\{\hat{N}_\tau=0\}} e^{\lambda\tau} \left( \int_0^\tau f_{\lambda\beta}(y + B_s) ds \right) \right] + O(\theta^2).$$

Besides,

$$\begin{aligned} \mathbb{E} \left[ \theta^{\hat{N}_1} e^{-\lambda(\theta-1)} 1_{\{\hat{T}_1 < \tau\}} \left( L_\tau^{-y}(B) - L_{\hat{T}_1}^{-y}(B) \right) \right] &= \mathbb{E} \left[ \theta^{\hat{N}_\tau} e^{-\lambda\tau(\theta-1)} 1_{\{\hat{T}_1 < \tau\}} \left( L_\tau^{-y}(B) - L_{\hat{T}_1}^{-y}(B) \right) \right] \\ &= \theta \mathbb{E} \left[ e^{\lambda\tau} 1_{\{\hat{N}_\tau=1\}} \left( L_\tau^{-y}(B) - L_{\hat{T}_1}^{-y}(B) \right) \right] + O(\theta^2). \end{aligned}$$

We then have

$$\bar{v}_{\lambda, \beta, \theta}(y) = \theta^{3/2} v_{\lambda, \beta}(y) + o(\theta^{3/2})$$

with

$$v_{\lambda, \beta}(y) = \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left[ e^{\lambda\tau} 1_{\{\hat{N}_\tau=0\}} \int_0^\tau f_{\lambda\beta}(y + B_s) ds + \frac{\beta}{2} e^{\lambda\tau} 1_{\{\hat{N}_\tau=1\}} \left( L_\tau^{-y}(B) - L_{\hat{T}_1}^{-y}(B) \right) \right].$$

Finally, we obtain

$$P(T - \theta, b(T)e^{a\sqrt{\theta}}) - (K - b(T)e^{a\sqrt{\theta}}) = \theta^{3/2} (\sigma b(T) \hat{\delta}) v_{\lambda, \beta} \left( \frac{a}{\sigma} \right) + o(\theta^{3/2}). \quad \blacksquare$$

**4.3. Convergence rate of the critical price.** Thanks to the expansion given in Theorem 4.3, we are now able to state the first main result of this paper.

**Theorem 4.7.** *Under the hypothesis of the model and  $\bar{d} < 0$ , we have as follows.*

If  $\nu\{\ln \frac{K}{b(T)}\} = 0$ , then we have

$$\lim_{t \rightarrow T} \frac{b(T) - b(t)}{\sigma b(T) \sqrt{(T-t)}} = y_0$$

with  $y_0 = -\sup\{x \in \mathbb{R} ; v_0(x) = \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E}(\int_0^\tau (x + B_s) ds) = 0\}$ .

If  $\nu\{\ln \frac{K}{b(T)}\} > 0$ , we then have

$$\lim_{t \rightarrow T} \frac{b(T) - b(t)}{\sigma b(T) \sqrt{(T-t)}} = y_{\lambda,\beta}$$

with  $y_{\lambda,\beta}$  as defined in Lemma 4.1, with

$$\lambda = \nu\left\{\ln \frac{K}{b(T)}\right\}, \quad \beta = \frac{K}{b(T)\hat{\delta}} \quad \text{and} \quad \hat{\delta} = \delta + \int_{y > \ln(K/b(T))} e^y \nu(dy).$$

*Proof of Theorem 4.7.*

According to Theorem 4.3, we have for all  $a < 0$ ,

$$P(T - \theta, b(T)e^{a\sqrt{\theta}}) = (K - b(T)e^{a\sqrt{\theta}})^+ + C\theta^{\frac{3}{2}}v_{\lambda,\beta}\left(\frac{a}{\sigma}\right) + o(\theta^{\frac{3}{2}}).$$

**Lower bound for  $b(T) - b(t)$ .** Specifically, we have for all  $a > -\sigma y_{\lambda,\beta}$ , where  $y_{\lambda,\beta}$  is defined by Lemma 4.1,

$$v_{\lambda,\beta}\left(\frac{a}{\sigma}\right) > 0;$$

we thus obtain for  $\theta$  close to 0,

$$P(t, b(T)e^{a\sqrt{\theta}}) > (K - b(T)e^{a\sqrt{\theta}}),$$

and then

$$\ln(b(T)) + a\sqrt{\theta} > \ln(b(t)),$$

hence

$$\frac{b(T) - b(t)}{b(t)\sqrt{\theta}} > -a.$$

Noting that since  $r > 0$  we have  $b(T) > 0$ , and by making  $t$  tend to  $T$ , then  $a$  to  $-\sigma y_{\lambda,\beta}$ , we obtain

$$\liminf_{t \rightarrow T} \frac{b(T) - b(t)}{b(T)\sqrt{T-t}} \geq \sigma y_{\lambda,\beta}.$$

**Upper bound for  $b(T) - b(t)$ .** Let's consider  $a \leq -\sigma y_{\lambda,\beta}$ . We thus have  $\nu_{\lambda,\beta}(\frac{a}{\sigma}) = 0$  and consequently,

$$P(t, b(T)e^{a\sqrt{\theta}}) - (K - b(T)e^{a\sqrt{\theta}}) = g(\theta)$$

with  $g(\theta) = o(\theta^{\frac{3}{2}})$ .

In addition, we have for all  $b(t) < x < K$ ,

$$P(t, x) - P(t, b(t)) - (x - b(t)) \frac{\partial P}{\partial x}(t, b(t)) = \int_{b(t)}^x (u - b(t)) \frac{\partial^2 P}{\partial x^2}(t, du)$$

since  $\frac{\partial^2 P}{\partial x^2}(t, du)$  is a positive measure on  $]0, +\infty[$ . As the smooth fit is satisfied,  $\frac{\partial P}{\partial x}(t, b(t)) = -1$  (see [8]), we have for all  $b(t) < x < K$ ,

$$P(t, x) - (K - x) = \int_{b(t)}^x (u - b(t)) \frac{\partial^2 P}{\partial x^2}(t, du).$$

Then, for  $b(t) < x = b(T)e^{a\sqrt{\theta}}$ , we have according to Lemma 3.2,

$$\begin{aligned} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) &\geq b(T) \hat{\delta} \left( (1 - e^{a\sqrt{\theta}}) - \lambda \beta \sqrt{\theta} \sigma \mathbb{E} \left( B_1 + \frac{a}{\sigma} \right)^+ \right) + o(\sqrt{\theta}) \\ &\geq b(T) \hat{\delta} \sqrt{\theta} \sigma \left( -\frac{a}{\sigma} - \lambda \beta \mathbb{E} \left( B_1 + \frac{a}{\sigma} \right)^+ \right) + o(\sqrt{\theta}). \end{aligned}$$

Hence

$$P(t, x) - (K - x) \geq [(x - b(t))^+]^2 b(T) \hat{\delta} \left( \frac{C(-\frac{a}{\sigma})}{b(0)^2 \sigma} \sqrt{\theta} + o(\sqrt{\theta}) \right),$$

where  $C(x) = x - \lambda \beta \mathbb{E}(B_1 - x)^+$ . Due to Lemma 4.2 and to the continuity of  $C(x)$ , we have, for  $-\frac{a}{\sigma}$  close enough to  $y_{\lambda,\beta}$ ,  $C(-\frac{a}{\sigma}) > 0$ . Moreover,

$$P(t, b(T)e^{a\sqrt{\theta}}) - (K - b(T)e^{a\sqrt{\theta}}) = g(\theta) = o(\theta^{\frac{3}{2}}).$$

Therefore, for  $\theta$  small enough, there exists a positive constant  $A$  such that

$$(17) \quad [(b(T)e^{a\sqrt{\theta}} - b(t))^+]^2 \leq A b(0)^2 \sigma^2 \frac{g(\theta)}{C(-\frac{a}{\sigma}) \sqrt{\theta}} = o(\theta),$$

$$(b(T)e^{a\sqrt{\theta}} - b(t))^+ = o(\sqrt{\theta}),$$

and then, for  $\theta$  small enough,

$$\frac{b(T) - b(t)}{b(T) \sqrt{\theta}} \leq -a + o(1).$$

Finally, by making  $a$  tend to  $-\sigma y_{\lambda,\beta}$ , we obtain

$$\limsup_{t \rightarrow T} \frac{b(T) - b(t)}{b(T) \sqrt{T - t}} \leq \sigma y_{\lambda,\beta}. \quad \blacksquare$$

**5. Limit case.** In this part, we consider the limit case where  $\bar{d} = r - \delta - \int_{y>0} (e^y - 1)\nu(dy) = 0$ . We then have the next theorem.

**Theorem 5.1.** *According to the model hypothesis, if  $\bar{d} = 0$ , then we have*

$$\lim_{t \rightarrow T} \frac{K - b(t)}{\sigma K \sqrt{(T - t)|\ln(T - t)|}} = \sqrt{2}.$$

The method for proving Theorem 5.1 consists (as in the Black–Scholes case) of analyzing the behavior of the European critical price  $b_e(t)$  introduced in section 1. Afterward we prove that the behavior of the critical price  $b(t)$  is similar by controlling the difference  $b(t) - b_e(t)$ .

Let us denote

$$\alpha(\theta) = \frac{\ln\left(\frac{K}{b_e(t)}\right) - \mu\theta}{\sigma\sqrt{\theta}},$$

where  $\mu = \gamma_0 - \frac{\sigma^2}{2} = r - \delta - \int (e^y - 1)\nu(dy) - \frac{\sigma^2}{2}$ .

**Proposition 5.1.** *Under the model hypothesis, if  $\bar{d} = 0$ , then we have*

- (i)  $\alpha(\theta) \sim \sqrt{2 \ln\left(\frac{1}{\theta}\right)}$ ,
- (ii)  $\lim_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sigma K \sqrt{|\theta \ln(\theta)|}} = \sqrt{2}$ .

*Proof of Proposition 5.1.* Since  $b(t) \leq b_e(t) \leq K$  and  $b(t) \rightarrow K$ , we clearly have

$$\sqrt{\theta}\alpha(\theta) \xrightarrow{\theta \rightarrow 0} 0.$$

We will first prove that  $\alpha(\theta) \xrightarrow{\theta \rightarrow 0} +\infty$  or, equivalently,

$$(18) \quad \lim_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sigma\sqrt{\theta}} = +\infty.$$

We have

$$(19) \quad K - b_e(t) = e^{-r\theta} \mathbb{E} \left[ \left( K - b_e(t) e^{\tilde{X}_\theta} \right)^+ \right].$$

Therefore

$$\begin{aligned} \frac{K - b_e(t)}{\sqrt{\theta}} &= e^{-r\theta} \mathbb{E} \left[ \left( \frac{K - b_e(t)}{\sqrt{\theta}} + b_e(t) \frac{1 - e^{\tilde{X}_\theta}}{\sqrt{\theta}} \right)^+ \right] \\ &= e^{-r\theta} \mathbb{E} \left[ \left( \frac{K - b_e(t)}{\sqrt{\theta}} + b_e(t) \frac{1 - e^{\sigma\sqrt{\theta}B_1 + \mu\theta + Z_\theta}}{\sqrt{\theta}} \right)^+ \right]. \end{aligned}$$

Now, if we notice that  $\frac{1 - e^{\sigma\sqrt{\theta}B_1 + \mu\theta + Z_\theta}}{\sqrt{\theta}} \xrightarrow{\theta \rightarrow 0} -\sigma B_1$ , we have by the Fatou lemma

$$\begin{aligned} \liminf_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sqrt{\theta}} &\geq \mathbb{E} \left[ \left( \liminf_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sqrt{\theta}} - \sigma K B_1 \right)^+ \right] \\ &= \liminf_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sqrt{\theta}} + \mathbb{E} \left[ \left( \sigma K B_1 - \liminf_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sqrt{\theta}} \right)^+ \right], \end{aligned}$$

which is equivalent to

$$\mathbb{E} \left[ \left( \sigma K B_1 - \liminf_{\theta \rightarrow 0} \frac{K - b_e(t)}{\sqrt{\theta}} \right)^+ \right] \leq 0.$$

This gives (18), which yields the wanted result.

(i) We now rewrite (19) to obtain

$$K - b_e(t) = e^{-r\theta} K - b_e(t)e^{-\delta\theta} + e^{-r\theta} \mathbb{E} \left[ \left( b_e(t)e^{\tilde{X}_\theta} - K \right)^+ \right],$$

and therefore

$$(20) \quad e^{-r\theta} \mathbb{E} \left[ \left( e^{\tilde{X}_\theta} - e^{\ln(\frac{K}{b_e(t)})} \right)^+ \right] = \frac{K}{b_e(t)} (1 - e^{-r\theta}) - (1 - e^{-\delta\theta}).$$

We will give an expansion for each side of the equation. For the left-hand side of the equation, we have

$$\begin{aligned} & e^{-r\theta} \mathbb{E} \left[ \left( e^{\tilde{X}_\theta} - e^{\ln(\frac{K}{b_e(t)})} \right)^+ \right] \\ &= e^{-r\theta + \theta\mu + \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E} \left[ \left( e^{\sigma\sqrt{\theta}B_1 + Z_\theta - \sigma\alpha(\theta)\sqrt{\theta}} - 1 \right)^+ \right] \\ &= e^{-r\theta + \theta\mu + \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E} \left[ (U_\theta e^{Z_\theta} - 1)^+ \right], \end{aligned}$$

where  $U_\theta = e^{\sigma\sqrt{\theta}B_1 - \sigma\alpha(\theta)\sqrt{\theta}}$ . Since the process  $Z_t$  is independent of  $U_\theta$ , we can write

$$\begin{aligned} & \mathbb{E} \left[ (U_\theta e^{Z_\theta} - 1)^+ | U_\theta \right] \\ &= (U_\theta - 1)^+ + \mathbb{E} \left[ \int_0^\theta ds \int \left( (U_\theta e^{Z_s + y} - 1)^+ - (U_\theta e^{Z_s} - 1)^+ \right) \nu(dy) | U_\theta \right] \\ &= (U_\theta - 1)^+ + \int_0^\theta ds \int \left( (U_\theta e^y - 1)^+ - (U_\theta - 1)^+ \right) \nu(dy) + U_\theta O(\theta^2), \end{aligned}$$

where  $O(\theta^2)$  is deterministic. Indeed,

$$\begin{aligned} & \left| \mathbb{E} \left[ \int_0^\theta ds \int \left( (U_\theta e^y e^{Z_s} - 1)^+ - (U_\theta e^y - 1)^+ \right) \nu(dy) | U_\theta \right] \right| \\ & \leq U_\theta \int e^y \nu(du) \int_0^\theta \mathbb{E} |e^{Z_s} - 1| ds = U_\theta O(\theta^2). \end{aligned}$$

Taking the expectation, we thus obtain

$$\begin{aligned} & \mathbb{E} \left[ (U_\theta e^{Z_\theta} - 1)^+ \right] \\ &= \mathbb{E} \left[ (U_\theta - 1)^+ \right] + \theta \int \mathbb{E} \left[ (U_\theta e^y - 1)^+ \right] \nu(dy) - \nu(\mathbb{R})\theta \mathbb{E} \left[ (U_\theta - 1)^+ \right] + O(\theta^2). \end{aligned}$$

Since  $\alpha(\theta) \rightarrow \infty$ , we have like in [6]

$$\mathbb{E} [(U_\theta - 1)^+] \sim \sigma\sqrt{\theta}\mathbb{E} (B_1 - \alpha(\theta))^+ = o(\sqrt{\theta}),$$

then

$$\mathbb{E} [(U_\theta e^{Z_\theta} - 1)^+] = \mathbb{E} [(U_\theta - 1)^+] + \theta \int \mathbb{E} [(U_\theta e^y - 1)^+] \nu(dy) + o(\theta^{\frac{3}{2}}).$$

We recall that  $U_\theta = e^{\sigma\sqrt{\theta}B_1 - \sigma\alpha(\theta)\sqrt{\theta}}$ , then

$$\begin{aligned} & \mathbb{E} [(U_\theta e^y - 1)^+] - \left( e^{y - \sigma\alpha(\theta)\sqrt{\theta}} - 1 \right)^+ \\ & \leq e^{y - \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E} \left| e^{\sigma\sqrt{\theta}B_1} - 1 \right| = e^y O(\sqrt{\theta}). \end{aligned}$$

Hence,

$$\begin{aligned} & \mathbb{E} [(U_\theta e^{Z_\theta} - 1)^+] \\ & = \mathbb{E} [(U_\theta - 1)^+] + \theta \int \left( e^{y - \sigma\alpha(\theta)\sqrt{\theta}} - 1 \right)^+ \nu(dy) + O(\theta^{\frac{3}{2}}) \\ & = \mathbb{E} [(U_\theta - 1)^+] + \theta \int_{y>0} \left( e^{y - \sigma\alpha(\theta)\sqrt{\theta}} - 1 \right) \nu(dy) \\ & \quad - \theta \int_{0 < y < \sigma\alpha(\theta)\sqrt{\theta}} \left( e^{y - \sigma\alpha(\theta)\sqrt{\theta}} - 1 \right) \nu(dy) + O(\theta^{\frac{3}{2}}). \end{aligned}$$

Since  $(1 - e^{-x}) \leq x$ , we then have

$$\left| \int_{(0, \sigma\alpha(\theta)\sqrt{\theta})} \left( e^{y - \sigma\alpha(\theta)\sqrt{\theta}} - 1 \right) \nu(dy) \right| \leq \underbrace{\nu\{0 < y < \sigma\alpha(\theta)\sqrt{\theta}\}}_{\xrightarrow{\theta \rightarrow 0} 0} \sigma\alpha(\theta)\sqrt{\theta},$$

$= o(\alpha(\theta)\theta^{\frac{1}{2}})$

and noticing that  $\theta^{\frac{3}{2}} = o(\alpha(\theta)\theta^{\frac{3}{2}})$ , we obtain

$$\mathbb{E} (U_\theta e^{Z_\theta} - 1)^+ = \mathbb{E} (U_\theta - 1)^+ + \theta \int (e^y - 1)^+ \nu(dy) - \alpha(\theta)\theta^{\frac{3}{2}} \sigma \int_{y>0} e^y \nu(dy) + o(\alpha(\theta)\theta^{\frac{3}{2}}).$$

The left-hand side of (20) becomes

$$\begin{aligned} & e^{-r\theta} \mathbb{E} \left[ \left( e^{\tilde{X}_\theta} - e^{\ln(\frac{K}{be(\tilde{v})})} \right)^+ \right] = e^{-r\theta + \theta\mu + \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E} [(U_\theta e^{Z_\theta} - 1)^+] \\ & = e^{-r\theta + \theta\mu + \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E} [(U_\theta - 1)^+] \\ & \quad + \left( 1 + \sigma\alpha(\theta)\sqrt{\theta} + o(\alpha(\theta)\sqrt{\theta}) \right) \left( \theta \int (e^y - 1)^+ \nu(dy) - \alpha(\theta)\theta^{\frac{3}{2}} \sigma \int_{y>0} e^y \nu(dy) + o(\alpha(\theta)\theta^{\frac{3}{2}}) \right) \\ & = e^{-r\theta + \theta\mu + \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E} [(U_\theta - 1)^+] + \theta \int (e^y - 1)^+ \nu(dy) - \nu(\mathbb{R}^+) \sigma\alpha(\theta)\theta^{\frac{3}{2}} + o(\alpha(\theta)\theta^{\frac{3}{2}}). \end{aligned}$$

(21)

Besides, the right-hand side of (20)

$$\begin{aligned}
 & \frac{K}{b_e(t)}(1 - e^{-r\theta}) - (1 - e^{-\delta\theta}) = e^{\sigma\sqrt{\theta}\alpha(\theta) + \mu\theta} r\theta - \delta\theta + O(\theta^2) \\
 & = (r - \delta)\theta + r\sigma\theta^{\frac{3}{2}}\alpha(\theta) + o(\theta^{\frac{3}{2}}\alpha(\theta)) \\
 (22) \quad & = \left( \int (e^y - 1)^+ \nu(dy) \right) \theta + r\sigma\alpha(\theta)\theta^{\frac{3}{2}} + o(\theta^{\frac{3}{2}}\alpha(\theta)).
 \end{aligned}$$

Thanks to (21) and (22), (20) becomes

$$e^{-r\theta + \theta\mu + \sigma\alpha(\theta)\sqrt{\theta}} \mathbb{E}[(U_\theta - 1)^+] = \sigma(r + \nu(\mathbb{R}^+))\alpha(\theta)\theta^{\frac{3}{2}} + o(\theta^{\frac{3}{2}}\alpha(\theta)).$$

Hence,

$$\mathbb{E}[(U_\theta - 1)^+] \sim \sigma(r + \nu(\mathbb{R}^+))\alpha(\theta)\theta^{\frac{3}{2}}.$$

As explained above, thanks to Proposition 2.1 in [14], we have

$$\mathbb{E}[(U_\theta - 1)^+] \sim \sigma\sqrt{\theta}\mathbb{E}(B_1 - \alpha(\theta))^+ \sim \frac{\sigma\sqrt{\theta}}{\sqrt{2\pi}\alpha^2(\theta)e^{\frac{\alpha^2(\theta)}{2}}}.$$

Thus, we have

$$(23) \quad \frac{1}{\sqrt{2\pi}\alpha^2(\theta)e^{\frac{\alpha^2(\theta)}{2}}} \sim (r + \nu(\mathbb{R}^+))\theta\alpha(\theta),$$

hence

$$(24) \quad \alpha(\theta) \sim \sqrt{2\ln\left(\frac{1}{\theta}\right)}.$$

(ii) Since  $\frac{K - b_e(t)}{K\sigma\sqrt{\theta}} \sim \alpha(\theta)$ , we obtain

$$\frac{K - b_e(t)}{\sigma K} \sim \sqrt{2\theta\ln\left(\frac{1}{\theta}\right)}.$$

To compare the behaviors of  $b(t)$  and  $b_e(t)$ , we have to control the difference between them.

**Proposition 5.2.** *According to the model hypothesis, if  $\bar{d} = 0$ , then there exists  $C > 0$  such that*

$$0 \leq \frac{b_e(t) - b(t)}{\sqrt{T - t}} \leq C.$$

Before proving Proposition 5.2, we need to prove the nondecreasing of  $b_e(t)$  near maturity, which is the purpose of this following lemma

**Lemma 5.2.** *The critical European put price,  $b_e(t)$ , is differentiable on  $(0, T)$  and for  $t$  close to  $T$ , we have*

$$b'_e(t) \geq 0.$$

*Proof of Lemma 5.2.* We recall that  $F$  is the function defined by  $F(t, x) = P_e(t, x) - (K - x)$ , and  $F$  is  $\mathcal{C}^1$  on  $(0, T) \times (0, K)$  and satisfies  $\frac{\partial F}{\partial x}(t, x) = \frac{\partial P_e}{\partial x}(t, x) + 1 > 0$ . Due to its definition,  $b_e(t)$  satisfies the following equation:  $P_e(t, b_e(t)) - (K - b_e(t)) = 0$ . Then, thanks to the implicit function theorem,  $b_e(t)$  is differentiable on  $(0, T)$  and

$$b'_e(t) = -\frac{\frac{\partial F}{\partial t}(t, b_e(t))}{\frac{\partial F}{\partial x}(t, b_e(t))} = -\frac{\frac{\partial P_e}{\partial t}(t, b_e(t))}{\frac{\partial P_e}{\partial x}(t, b_e(t)) + 1},$$

which means that

$$-b'_e(t) \frac{\partial P_e}{\partial t}(t, b_e(t)) \geq 0.$$

We will study the sign of  $\frac{\partial P_e}{\partial t}(t, b_e(t))$  instead of that of  $b'_e(t)$ .

The European put price satisfies the following equation:

$$\begin{aligned} & \frac{\partial P_e}{\partial t}(t, b_e(t)) \\ &= rP_e(t, b_e(t)) - \frac{\sigma^2 b_e(t)^2}{2} \frac{\partial^2 P_e}{\partial x^2}(t, b_e(t)) - (r - \delta) b_e(t) \frac{\partial P_e}{\partial x}(t, b_e(t)) \\ & \quad - \int \left[ P_e(t, b_e(t) e^y) - P_e(t, b_e(t)) - b_e(t)(e^y - 1) \frac{\partial P_e}{\partial x}(t, b_e(t)) \right] \nu(dy) \\ &= r(K - b_e(t)) - \frac{\sigma^2 b_e(t)^2}{2} \frac{\partial^2 P_e}{\partial x^2}(t, b_e(t)) - \underbrace{\left( r - \delta - \int_{\bar{d}=0} (e^y - 1)^+ \nu(dy) \right)}_{\bar{d}=0} b_e(t) \frac{\partial P_e}{\partial x}(t, b_e(t)) \\ & \quad - \int_{y>0} P_e(t, b_e(t) e^y) \nu(dy) + \nu(\mathbb{R}_+) P_e(t, b_e(t)) \\ & \quad - \int_{y<0} \left[ P_e(t, b_e(t) e^y) - P_e(t, b_e(t)) - b_e(t)(e^y - 1) \frac{\partial P_e}{\partial x}(t, b_e(t)) \right] \nu(dy). \end{aligned}$$

Since  $P_e(t, \cdot)$  is a nonnegative convex function, we have  $\int_{y>0} [P_e(t, b_e(t) e^y)] \nu(dy) \geq 0$  and

$$\int_{y<0} \left[ P_e(t, b_e(t) e^y) - P_e(t, b_e(t)) - b_e(t)(e^y - 1) \frac{\partial P_e}{\partial x}(t, b_e(t)) \right] \nu(dy) \geq 0,$$

so that

$$\frac{\partial P_e}{\partial t}(t, b_e(t)) \leq (r + \nu(\mathbb{R}^+)) (K - b_e(t)) - \frac{\sigma^2 b_e(t)^2}{2} \frac{\partial^2 P_e}{\partial x^2}(t, b_e(t)).$$

Thanks to Proposition 5.1, we have an expansion for  $(K - b_e(t))$ . Now, let's have a look at the estimate of  $\frac{\partial^2 P_e}{\partial x^2}(t, b_e(t))$  near  $T$ . We have

$$\begin{aligned} \frac{\partial P_e}{\partial x}(t, x) &= -e^{-r(T-t)} \mathbb{E} \left[ e^{\tilde{X}_{T-t}} \mathbf{1}_{\{K - x e^{\tilde{X}_{T-t}} > 0\}} \right] \\ &= -e^{-r(T-t)} \int_{-\infty}^{\ln(\frac{K}{x})} e^u p_{\tilde{X}_{T-t}}(u) du, \end{aligned}$$



where  $p_X$  denotes the density of  $X$  and  $\tilde{X}_t = \mu(t) + \sigma B_t + Z_t$ . Then, we have

$$\begin{aligned} \frac{\partial^2 P_e}{\partial x^2}(t, x) &= e^{-r(T-t)} \frac{K}{x^2} p_{\tilde{X}_{T-t}} \left( \ln \left( \frac{K}{x} \right) \right) \\ &\geq e^{-r(T-t)} \frac{K}{x^2} p_{\mu(T-t) + \sigma B_{T-t}} \left( \ln \left( \frac{K}{x} \right) \right) \mathbb{P}(T_1 > \theta) \\ &= e^{-r\theta} \frac{K}{x^2 \sigma \sqrt{2\pi\theta}} e^{-\frac{1}{2} \left( \frac{\ln(K/x) - \mu\theta}{\sigma\sqrt{\theta}} \right)^2} \mathbb{P}(T_1 > \theta). \end{aligned}$$

Then,

$$\frac{\partial P_e}{\partial t}(t, b_e(t)) \leq (r + \nu(\mathbb{R}^+)) (K - b_e(t)) - e^{-r\theta} \frac{\sigma K}{2\sqrt{2\pi\theta}} e^{-\frac{\alpha(\theta)^2}{2}} \mathbb{P}(T_1 > \theta).$$

We can easily check that  $K - b_e(t) \sim \sigma K \sqrt{\theta} \alpha(\theta) = o(\alpha^3(\theta) \sqrt{\theta})$ , and we recall the equivalency (23)

$$\frac{1}{\sqrt{2\pi} \alpha^2(\theta) e^{\frac{\alpha^2(\theta)}{2}}} \sim (r + \nu(\mathbb{R}^+)) \theta \alpha(\theta),$$

which yields

$$e^{-r\theta} \frac{\sigma K}{2\sqrt{2\pi\theta}} e^{-\frac{\alpha(\theta)^2}{2}} \mathbb{P}(T_1 > \theta) \sim \sigma K \frac{e^{-\frac{\alpha^2(\theta)}{2}}}{2\sqrt{2\pi\theta}} \sim \frac{\sigma K}{2} (r + \nu(R^+)) \alpha^3(\theta) \sqrt{\theta}.$$

Then, we have, for  $\theta$  small enough

$$\frac{\partial P_e}{\partial t}(t, b_e(t)) \leq -\frac{\sigma K}{2} (r + \nu(R^+)) \alpha^3(\theta) \sqrt{\theta} + o(\alpha^3(\theta) \sqrt{\theta}) < 0,$$

which proves that  $b'_e(t)$  is a nondecreasing function for  $t$  close to  $T$ .  $\blacksquare$

We are now in a position to prove Proposition 5.2.

*Proof of Proposition 5.2.* An expansion of  $P(t, x)$  around  $(t, b(t))$  gives

$$P(t, x) - P(t, b(t)) - (x - b(t)) \frac{\partial P}{\partial x}(t, b(t)) = \int_{b(t)}^x (u - b(t)) \frac{\partial^2 P}{\partial x^2}(t, du),$$

and thanks to the smooth fit which is satisfied at  $b(t)$ , we obtain

$$P(t, x) - (K - x) \geq \frac{(x - b(t))^2}{2} \inf_{b(t) \leq u \leq x} \frac{\partial^2 P}{\partial x^2}(t, u).$$

First, we are going to give, as in Lemma 3.2, a lower bound for  $\inf_{b(t) \leq u \leq b_e(t)} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u)$ . The variational inequality gives, for  $u \in (b(t), K)$ ,

$$\begin{aligned} &\frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \\ &\geq rP(t, u) - (r - \delta) u \frac{\partial P}{\partial x}(t, u) - \int \left( P(t, ue^y) - P(t, u) - u(e^y - 1) \frac{\partial P}{\partial x}(t, u) \right) \nu(dy) \\ &\geq r(K - u) - \left( r - \delta - \int_{y>0} (e^y - 1) \nu(dy) \right) u \frac{\partial P}{\partial x}(t, u) - \int_{y>0} P(t, ue^y) - P(t, u) \nu(dy) \\ &\quad - \int_{y<0} \left( P(t, ue^y) - (K - u) - u(e^y - 1) \frac{\partial P}{\partial x}(t, u) \right) \nu(dy). \end{aligned}$$

Since  $P(t, \cdot)$  is nonincreasing and  $\bar{d} = 0$ , we obtain

$$\begin{aligned} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) &\geq r(K - u) - \int_{y < 0} \left( P(t, ue^y) - (K - u) - u(e^y - 1) \frac{\partial P}{\partial x}(t, u) \right) \nu(dy) \\ &= r(K - u) - \int_{y < 0} P(t, ue^y) - (K - ue^y) \nu(dy) - u \left( \frac{\partial P}{\partial x}(t, u) + 1 \right) \left( \int_{y < 0} (1 - e^y) \nu(dy) \right). \end{aligned}$$

Thanks to the convexity of  $P$ ,  $\frac{\partial P}{\partial x}(t, u)$  is nondecreasing and  $\frac{\partial P}{\partial x}(t, u) \geq -1$ . We then have, for all  $t < T$ ,

$$\begin{aligned} \inf_{b(t) \leq u \leq b_e(t)} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) &\geq r(K - b_e(t)) - \int_{y < 0} P(t, b_e(t)e^y) - (K - b_e(t)e^y) \nu(dy) \\ &\quad - b_e(t) \left( \frac{\partial P}{\partial x}(t, b_e(t)) + 1 \right) \left( \int_{y < 0} (1 - e^y) \nu(dy) \right) \\ &\geq r(K - b_e(t)) - \int_{y < 0} P_e(t, b_e(t)e^y) - (K - b_e(t)e^y) \nu(dy) + o(\sqrt{\theta}). \end{aligned}$$

We obtained the last inequality, using the estimate of  $e(\theta, x) = O(\theta)$  and  $\frac{\partial P}{\partial x}(t, x) + 1 = o(\sqrt{\theta})$  (see Lemma 3.1). Since  $y < 0$ , we also have  $P_e(t, b_e(t)e^y) - (K - b_e(t)e^y) \leq 0$ , thus

$$\inf_{b(t) \leq u \leq b_e(t)} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \geq r(K - b_e(t)) + o(\sqrt{\theta}).$$

Besides, for  $\theta$  small enough, we have  $\sqrt{\theta} \leq K - b_e(t)$ , and then we obtain

$$P(t, b_e(t)) - (K - b_e(t)) \geq \frac{(b_e(t) - b(t))^2}{b_e^2(t) \sigma^2} r(K - b_e(t)) (1 + o(1)).$$

Furthermore,

$$\begin{aligned} P(t, b_e(t)) - (K - b_e(t)) &= e(\theta, b_e(t)) \\ &= \mathbb{E} \left\{ \int_0^\theta e^{-rs} \left( rK - \delta S_s^{b_e(t)} - \int_{y > 0} P(t + s, S_s^{b_e(t)} e^y) - (K - S_s^{b_e(t)} e^y) \nu(dy) \right) 1_{\{S_s^{b_e(t)} < b(t+s)\}} ds \right\} \\ &\leq \mathbb{E} \left\{ \int_0^\theta e^{-rs} \left( rK - \delta S_s^{b_e(t)} - \int_{y > 0} (S_s^{b_e(t)} e^y - K)^+ \nu(dy) \right) 1_{\{S_s^{b_e(t)} < b(t+s)\}} ds \right\}. \end{aligned}$$

Since  $\delta = r - \int_{y > 0} (e^y - 1) \nu(dy)$ , we have

$$\begin{aligned} 0 &\leq \left( rK - \delta x - \int_{y > 0} (xe^y - K)^+ \nu(dy) \right) 1_{\{x < b(t+s)\}} \\ &\leq \left( r(K - x) - \int_{y > 0} (xe^y - K)^+ - (xe^y - x)^+ \nu(dy) \right) 1_{\{x < K\}} \\ &\leq (r + \nu(\mathbb{R}^+)) (K - x)^+, \end{aligned}$$

thus,

$$\begin{aligned} e(\theta, b_e(t)) &\leq (r + \nu(\mathbb{R}^+)) \mathbb{E} \left\{ \int_0^\theta e^{-rs} \left( K - S_s^{b_e(t)} \right)^+ ds \right\} \\ &= (r + \nu(\mathbb{R}^+)) \int_0^\theta P_e(T - s, b_e(t)) ds \\ &= (r + \nu(\mathbb{R}^+)) \int_0^\theta P_e(t + u, b_e(t)) du. \end{aligned}$$

And as we saw in Lemma 5.2, near  $T$ ,  $b_e(t)$  is nondecreasing, then  $b_e(t) \leq b_e(t + u)$ . Due to the nondecreasing of  $P_e(t, x) - (K - x)$  on  $x$ , we thus have

$$P_e(t + u, b_e(t)) \leq K - b_e(t).$$

In conclusion, we have

$$e(\theta, b_e(t)) \leq (r + \nu(\mathbb{R}^+)) \theta (K - b_e(t))$$

and

$$e(\theta, b_e(t)) \geq \frac{[b_e(t) - b(t)]^2}{b_e^2(t) \sigma^2} r (K - b_e(t)) (1 + o(1)).$$

We conclude that there exists a positive constant  $C$  such that

$$\frac{b_e(t) - b(t)}{\sqrt{\theta}} \leq C. \quad \blacksquare$$

### Appendix A. Proofs of lemmas.

*Proof of Lemma 3.1.* According to the early exercise premium formula, we have

$$P(t, x) = P_e(t, x) + e(T - t, x)$$

and

$$e(\theta, x) = \mathbb{E} \left\{ \int_0^\theta e^{-rs} \Phi(t + s, x, S_s^1) 1_{\{x S_s^1 < b(t+s)\}} ds \right\}$$

with

$$\Phi(t, x) = rK - \delta x - \int_{y>0} (P(t, x e^y) - (K - x e^y)) \nu(dy).$$

Notice that  $\Phi$  is a continuous function and  $\|\Phi'_x\|_\infty \leq \delta + \int_{y>0} e^y \nu(dy)$ .

(1) It is obvious that  $0 \leq e(\theta, x) \leq \theta rK = O(\theta)$ , since  $0 \leq \Phi(t, x) 1_{\{x < b(t+s)\}} \leq rK$ .

(2) For all random variable  $X$ , we denote by  $p_X$  its density, and we thus have for all fixed  $s \in [0, \theta]$ ,

$$\begin{aligned} p_{-\tilde{X}_s}(x) &= p_{-\mu s - \sigma B_s} * p_{-Z_s}(x) = \frac{1}{\sqrt{s}} \frac{1}{\sigma \sqrt{2\pi}} \int e^{-\frac{(-x + \mu s - u)^2}{2\sigma^2 s}} p_{-Z_s}(u) du \\ (25) \quad &\leq C t e \frac{1}{\sqrt{s}}. \end{aligned}$$

We can state

$$(26) \quad \frac{\partial e}{\partial x}(\theta, x) = \mathbb{E} \left\{ \int_0^\theta e^{-rs} S_s^1 \Phi'_x(t+s, xS_s^1) 1_{\{xS_s^1 < b(t+s)\}} ds \right\} - \int_0^\theta \frac{\Phi(t+s, b(t+s))}{x} p_{-\tilde{X}_s} \left( \ln \left( \frac{x}{b(t+s)} \right) \right) ds.$$

Then, we have

$$\begin{aligned} \left| \frac{\partial e}{\partial x}(\theta, x) \right| &\leq \left| \mathbb{E} \left\{ \int_0^\theta e^{-rs} S_s^1 \Phi'_x(t+s, xS_s^1) 1_{\{xS_s^1 < b(t+s)\}} ds \right\} \right| \\ &\quad + \left| \int_0^\theta \frac{\Phi(t+s, b(t+s))}{x} p_{-\tilde{X}_s} \left( \ln \left( \frac{x}{b(t+s)} \right) \right) ds \right| \\ &\leq \|\Phi'_x\|_\infty \frac{b(T)}{x} \theta + \left| \int_0^\theta \frac{\Phi(t+s, b(t+s))}{x} p_{-\tilde{X}_s} \left( \ln \left( \frac{x}{b(t+s)} \right) \right) ds \right|. \end{aligned}$$

According to inequality (25), we also have

$$\begin{aligned} &\left| \int_0^\theta \frac{\Phi(t+s, b(t+s))}{x} p_{-\tilde{X}_s} \left( \ln \left( \frac{x}{b(t+s)} \right) \right) ds \right| \\ &\leq C^{te} \left| \int_0^\theta \frac{\Phi(t+s, b(t+s))}{x\sqrt{s}} ds \right| \\ &= \frac{C^{te}}{x} \theta \left| \int_0^1 \frac{\Phi(t+\theta u, b(t+\theta u))}{\sqrt{\theta u}} du \right| \\ &\leq \frac{C^{te}}{x} \sqrt{\theta} \sup_{t \leq u \leq t+\theta} |\Phi(u, b(u))| \int_0^1 \frac{1}{\sqrt{u}} du \\ &\leq \frac{C^{te}}{x} \sqrt{\theta} \sup_{T-\theta \leq u \leq T} |\Phi(u, b(u))| \int_0^1 \frac{1}{\sqrt{u}} du. \end{aligned}$$

However, thanks to the continuity of  $b(u)$  and of  $\Phi(t, x)$ , we have  $\lim_{\theta \rightarrow 0} \sup_{T-\theta \leq u \leq T} |\Phi(u, b(u))| = |\Phi(T, b(T))| = 0$ . Therefore, we conclude that  $|\frac{\partial e}{\partial x}(\theta, x)| = \frac{1}{x} o(\sqrt{\theta})$ .

(3) In view of the above estimate for  $\partial e / \partial x$ , in order to establish the second part of the lemma, it suffices to prove that, for  $x \in (0, b_e(t) \wedge b(T)]$ ,

$$(27) \quad 1 + \frac{\partial P_e}{\partial x}(t, x) = o(\sqrt{\theta}),$$

and, due to the convexity of  $P_e$ , it suffices to prove (27) for  $x = b(T) \wedge b_e(t)$ .

We have

$$\begin{aligned} 0 \leq \left( 1 + \frac{\partial P_e}{\partial x}(t, x) \right) &= 1 - e^{-r\theta} \mathbb{E} \left( e^{\tilde{X}_\theta} 1_{\{\tilde{X}_\theta < \ln \frac{K}{x}\}} \right) \\ &\leq 1 - \mathbb{E} \left( e^{\tilde{X}_\theta} 1_{\{\tilde{X}_\theta < \ln \frac{K}{x}\}} \right) + o(\sqrt{\theta}) \\ &= 1 - \mathbb{E} \left( e^{\mu\theta + \sigma B_\theta} 1_{\{\mu\theta + \sigma B_\theta < \ln \frac{K}{x}\}} \right) + o(\sqrt{\theta}), \end{aligned}$$

where the last equality is due to the fact that the probability that a jump occurs before  $\theta$  is  $O(\theta)$ .

If  $b(T) = K$ , then  $b_e(t) \wedge b(T) = b_e(t)$  and we have, using the notation of section 4,

$$\begin{aligned} 1 - \mathbb{E} \left( e^{\mu\theta + \sigma B_\theta} 1_{\{\mu\theta + \sigma B_\theta < \ln \frac{K}{b_e(t)}\}} \right) &= 1 - \mathbb{E} \left( e^{\sigma B_\theta} 1_{\{B_\theta < \sqrt{\theta}\alpha(\theta)\}} \right) + o(\sqrt{\theta}) \\ &= \mathbb{P}(B_\theta \geq \sqrt{\theta}\alpha(\theta)) - \mathbb{E} \left( \sigma B_\theta 1_{\{B_\theta < \sqrt{\theta}\alpha(\theta)\}} \right) + o(\sqrt{\theta}). \end{aligned}$$

Since  $\alpha(\theta) \xrightarrow{\theta \rightarrow 0} \infty$ , we have

$$\mathbb{E} \left( \sigma B_\theta 1_{\{B_\theta < \sqrt{\theta}\alpha(\theta)\}} \right) = \sigma\sqrt{\theta} \mathbb{E} \left( B_1 1_{\{B_1 < \alpha(\theta)\}} \right) = o(\sqrt{\theta}),$$

and using (23) and (24), we also have

$$\mathbb{P}(B_1 \geq \alpha(\theta)) \leq \frac{e^{-\frac{\alpha^2(\theta)}{2}}}{\alpha(\theta)} \leq C\theta\alpha^2(\theta) = O(\theta|\ln\theta|) = o(\sqrt{\theta}).$$

We now assume  $b(T) < K$ . In this case, we observe that with the notation  $x_t = b(T) \wedge b_e(t)$

$$\begin{aligned} 1 - \mathbb{E} \left( e^{\mu\theta + \sigma B_\theta} 1_{\{\mu\theta + \sigma B_\theta < \ln \frac{K}{x_t}\}} \right) &= 1 - \mathbb{E} \left( e^{\sigma\sqrt{\theta}B_1} 1_{\{B_1 < (\ln \frac{K}{x_t} - \mu\theta)/(\sigma\sqrt{\theta})\}} \right) + o(\theta) \\ &= 1 - e^{\sigma^2\theta/2} \mathbb{P} \left( B_1 < \frac{\ln(K/x_t) - \mu\theta}{\sigma\sqrt{\theta}} - \sigma\sqrt{\theta} \right) + o(\theta) \\ &= \mathbb{P} \left( B_1 > \frac{\ln(K/x_t) - \mu\theta}{\sigma\sqrt{\theta}} - \sigma\sqrt{\theta} \right) + o(\theta). \end{aligned}$$

If we prove that  $\limsup_{t \uparrow T} x_t < K$ , we will have  $\mathbb{P}(B_1 > \frac{\ln(K/x_t) - \mu\theta}{\sigma\sqrt{\theta}} - \sigma\sqrt{\theta}) = o(\theta^n)$  for all  $n > 0$  and the proof of the lemma will be completed. We have assumed  $b(T) < K$ . Therefore, we want to prove that  $\limsup_{t \uparrow T} b_e(T) < K$ . In fact, we will show that

$$(28) \quad \limsup_{t \uparrow T} b_e(T) \leq b(T).$$

Indeed, from the definition of  $b_e(t)$ , we have (see (20)), using Jensen's inequality,

$$\begin{aligned} K(1 - e^{-r\theta}) - b_e(t)(1 - e^{-\delta\theta}) &= e^{-r\theta} \mathbb{E} \left( b_e(t) e^{\tilde{X}_\theta} - K \right)^+ \\ &\geq e^{-r\theta} \mathbb{E} \left( b_e(t) e^{\gamma_0\theta + Z_\theta} - K \right)^+ \\ &\geq e^{-r\theta} \mathbb{E} \left[ 1_{\{N_\theta=1\}} \left( b_e(t) e^{\gamma_0\theta + Z_{T_1}} - K \right)^+ \right] \\ &= e^{-r\theta} \mathbb{P}(N_\theta = 1) \mathbb{E} \left[ \left( b_e(t) e^{\gamma_0\theta + Z_{T_1}} - K \right)^+ \right], \end{aligned}$$

where  $(N_t)_{t \geq 0}$  is the counting process of the jumps of  $Z$ . Dividing by  $\theta$ , we easily conclude that any limit  $\xi$  of  $b_e(t)$  as  $t \rightarrow T$  satisfies

$$rK - \delta\xi \geq \int (\xi e^y - K)^+ \nu(dy).$$

Hence  $\xi \leq b(T)$ , which proves (28).  $\blacksquare$

*Proof of Lemma 3.2.* Let be  $x \in (b(t), b(T))$ ; then the variational inequality gives, for almost  $u \in (b(t), x)$ ,

$$\begin{aligned} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) &\geq rP(t, u) - (r - \delta)u \frac{\partial P}{\partial x}(t, u) \\ &\quad - \int \left( P(t, ue^y) - P(t, u) - u(e^y - 1) \frac{\partial P}{\partial x}(t, u) \right) \nu(dy). \end{aligned}$$

Notice that  $P(t, u) \geq K - u$ ; thus

$$\begin{aligned} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) &\geq r(K - u) + (r - \delta)u \\ &\quad - \int (P(t, ue^y) - (K - u) + u(e^y - 1)) \nu(dy) \\ (29) \quad &\quad - u \left( \frac{\partial P}{\partial x}(t, u) + 1 \right) \left( (r - \delta) - \int (e^y - 1) \nu(dy) \right) \end{aligned}$$

And thanks to Lemma 3.1, we also have, for all  $b(0) \leq u \leq x \leq b_e(t) \wedge b(T)$ ,

$$\frac{\partial P}{\partial x}(t, u) + 1 = o(\sqrt{\theta}),$$

independently of  $u$ ; therefore,

$$(30) \quad \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \geq rK - \delta u - \int (P(t, ue^y) - (K - ue^y)) \nu(dy) + o(\sqrt{\theta}).$$

As the right-hand side of equality (30) is nonincreasing in  $u$ , we obtain

$$(31) \quad \inf_{b(t) \leq u \leq x} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \geq rK - \delta x - \int (P(t, xe^y) - (K - xe^y)) \nu(dy) + o(\sqrt{\theta}).$$

Notice that

$$\begin{aligned} \int P(t, xe^y) \nu(dy) &= P_e(t, xe^y) + e(\theta, xe^y) \\ &= \int \mathbb{E}(K - xe^y e^{X_\theta})^+ \nu(dy) + o(\sqrt{\theta}) \\ &= \int \mathbb{E}(K - xe^y (1 + \sigma B_\theta))^+ \nu(dy) + o(\sqrt{\theta}) \\ &= \int \mathbb{E}((K - xe^y) - xe^y \sigma B_\theta)^+ \nu(dy) + o(\sqrt{\theta}). \end{aligned}$$

We now consider the integral  $\int P(t, xe^y)\nu(dy)$  over the sets  $\{y < \ln(\frac{K}{b(T)})\}$ ,  $\{\ln(\frac{K}{b(T)}) < y\}$ , and  $\{y = \ln(\frac{K}{b(T)})\}$ . Then, on the set  $\{y < \ln(\frac{K}{b(T)})\}$ , we have

$$\begin{aligned} & \int_{\{y < \ln(\frac{K}{b(T)})\}} P(t, xe^y)\nu(dy) = \int_{\{y < \ln(\frac{K}{b(T)})\}} \mathbb{E}(K - xe^y) - xe^y\sigma B_\theta)^+ \nu(dy) + o(\sqrt{\theta}) \\ & = \int_{\{y < \ln(\frac{K}{b(T)})\}} (K - xe^y)\mathbb{P}(xe^y\sigma B_\theta < (K - xe^y))\nu(dy) \\ & \quad - \int_{\{y < \ln(\frac{K}{b(T)})\}} xe^y\sigma \mathbb{E}(B_\theta 1_{\{xe^y\sigma B_\theta < (K - xe^y)\}})\nu(dy) + o(\sqrt{\theta}) \\ & \leq \int_{\{y < \ln(\frac{K}{b(T)})\}} (K - xe^y)\nu(dy) - x\sigma\sqrt{\theta} \int_{\{y < \ln(\frac{K}{b(T)})\}} \frac{e^y \mathbb{E}\left(B_1 1_{\{B_1 < \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{x}e^{-y}-1)\}}\right)}{\nu(dy)} \nu(dy) + o(\sqrt{\theta}). \end{aligned}$$

For all  $y < \ln(\frac{K}{b(T)})$ , we have  $\frac{K}{x}e^{-y} - 1 > \frac{K}{b(T)}e^{-y} - 1 > 0$ ; therefore

$$\begin{aligned} 0 & \leq -\mathbb{E}\left(B_1 1_{\{B_1 < \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{x}e^{-y}-1)\}}\right) = \mathbb{E}\left(B_1 1_{\{B_1 \geq \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{x}e^{-y}-1)\}}\right) \\ & \leq \mathbb{E}\left(B_1 1_{\{B_1 \geq \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{b(T)}e^{-y}-1)\}}\right) \xrightarrow{\theta \rightarrow 0} 0. \end{aligned}$$

By the dominated convergence we obtain

$$(32) \quad \int_{\{y < \ln(\frac{K}{b(T)})\}} P(t, xe^y)\nu(dy) \leq \int_{\{y < \ln(\frac{K}{b(T)})\}} (K - xe^y)\nu(dy) + o(\sqrt{\theta}).$$

On the set  $\{y > \ln(\frac{K}{b(T)})\}$ , we have  $K < b(T)e^y$ , and therefore

$$\begin{aligned} & \int_{\{y > \ln(\frac{K}{b(T)})\}} P(t, xe^y)\nu(dy) = \int_{\{y > \ln(\frac{K}{b(T)})\}} \mathbb{E}((K - xe^y) - xe^y\sigma B_\theta)^+ \nu(dy) + o(\sqrt{\theta}) \\ & \leq \int_{\{y > \ln(\frac{K}{b(T)})\}} \mathbb{E}\left[\left(b(T)e^y - xe^y - xe^y\sigma\sqrt{\theta}B_1\right) 1_{\{xe^y\sigma\sqrt{\theta}B_1 < (K - xe^y)\}}\right] \nu(dy) + o(\sqrt{\theta}) \\ & = (b(T) - x) \int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \mathbb{P}\left(B_1 < \frac{1}{\sigma\sqrt{\theta}}\left(\frac{K}{x}e^{-y} - 1\right)\right) \nu(dy) \\ & \quad - \sqrt{\theta}x \int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \sigma \mathbb{E}\left(B_1 1_{\{B_1 < \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{x}e^{-y}-1)\}}\right) \nu(dy) + o(\sqrt{\theta}). \end{aligned}$$

Notice that for all  $y > \ln(\frac{K}{b(T)})$ , we have  $\frac{1}{\sigma\sqrt{\theta}}\left(\frac{K}{x}e^{-y} - 1\right) \leq \frac{1}{\sigma\sqrt{\theta}}\left(\frac{K}{b(t)}e^{-y} - 1\right) \rightarrow -\infty$ ; thus

$$\begin{aligned} \mathbb{P}\left(B_1 < \frac{1}{\sigma\sqrt{\theta}}\left(\frac{K}{x}e^{-y} - 1\right)\right) & \leq \mathbb{P}\left(B_1 < \frac{1}{\sigma\sqrt{\theta}}\left(\frac{K}{b(t)}e^{-y} - 1\right)\right) \\ & \xrightarrow{\theta \rightarrow 0} 0, \end{aligned}$$

and

$$\mathbb{E} \left( |B_1| 1_{\{B_1 < \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{x}e^{-y}-1)\}} \right) \leq \mathbb{E} \left( |B_1| 1_{\{B_1 < \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{b(t)}e^{-y}-1)\}} \right) \xrightarrow{\theta \rightarrow 0} 0.$$

Therefore, by dominated convergence, we obtain

$$\int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \mathbb{P} \left( B_1 < \frac{1}{\sigma\sqrt{\theta}} \left( \frac{K}{b(t)} e^{-y} - 1 \right) \right) \nu(dy) \xrightarrow{\theta \rightarrow 0} 0$$

and

$$-\sqrt{\theta}x \int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \sigma \mathbb{E} \left( B_1 1_{\{xe^y \sigma \sqrt{\theta} B_1 < (K - xe^y)\}} \right) \nu(dy) = o(\sqrt{\theta}).$$

Consequently, if we denote by  $\epsilon(\theta) = \int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \mathbb{P}(B_1 < \frac{1}{\sigma\sqrt{\theta}}(\frac{K}{b(t)}e^{-y} - 1)) \nu(dy)$ , we obtain

$$(33) \quad \int_{\{y > \ln(\frac{K}{b(T)})\}} P(t, xe^y) \nu(dy) \leq (b(T) - x)\epsilon(\theta) + o(\sqrt{\theta}),$$

with  $\epsilon(\theta) \xrightarrow{\theta \rightarrow 0} 0$ .

Finally, on the set  $\{y = \ln(\frac{K}{b(T)})\}$ , we have

$$\begin{aligned} \int_{\{\ln(\frac{K}{b(T)})\}} P(t, xe^y) \nu(dy) &= \int_{\{\ln(\frac{K}{b(T)})\}} \mathbb{E}((K - xe^y) - xe^y \sigma B_\theta)^+ \nu(dy) + o(\sqrt{\theta}) \\ &= \int_{\{\ln(\frac{K}{b(T)})\}} (K - xe^y) \nu(dy) + \int_{\{\ln(\frac{K}{b(T)})\}} \mathbb{E}(xe^y \sigma B_\theta - (K - xe^y))^+ \nu(dy) + o(\sqrt{\theta}) \\ &= \int_{\{\ln(\frac{K}{b(T)})\}} (K - xe^y) \nu(dy) + \int_{\{\ln(\frac{K}{b(T)})\}} xe^y \mathbb{E} \left( \sigma B_\theta - \left( \frac{K}{x} e^{-y} - 1 \right) \right)^+ \nu(dy) \\ &= \int_{\{\ln(\frac{K}{b(T)})\}} (K - xe^y) \nu(dy) + \frac{xK}{b(T)} \nu \left\{ \ln \left( \frac{K}{b(T)} \right) \right\} \mathbb{E} \left( \sigma B_\theta - \left( \frac{b(T)}{x} - 1 \right) \right)^+ \\ &\leq \int_{\{\ln(\frac{K}{b(T)})\}} (K - xe^y) \nu(dy) + K \nu \left\{ \ln \left( \frac{K}{b(T)} \right) \right\} \mathbb{E} \left( \sigma B_\theta - \ln \left( \frac{b(T)}{x} \right) \right)^+. \end{aligned}$$

We have thus proved that

$$\begin{aligned} \int P(t, xe^y) \nu(dy) &\leq \int_{\{y \leq \ln(\frac{K}{b(T)})\}} (K - xe^y) \nu(dy) + K \nu \left\{ \ln \left( \frac{K}{b(T)} \right) \right\} \mathbb{E} \left( \sigma B_\theta - \ln \left( \frac{b(T)}{x} \right) \right)^+ \\ &\quad + (b(T) - x) \epsilon(\theta) + o(\sqrt{\theta}). \end{aligned}$$



Going back to inequality (31), we obtain

$$\begin{aligned} & \int P(t, xe^y) - (K - xe^y)\nu(dy) \\ & \leq - \int_{\{y > \ln(\frac{K}{b(T)})\}} (K - xe^y)\nu(dy) + K\nu \left\{ \ln \left( \frac{K}{b(T)} \right) \right\} \mathbb{E} \left( \sigma B_\theta - \ln \left( \frac{b(T)}{x} \right) \right)^+ \\ & \quad + (b(T) - x) \epsilon(\theta) + o(\sqrt{\theta}). \end{aligned}$$

Finally, since  $rK = \delta b(T) + \int (b(t)e^y - K)^+ \nu(y)$ , we have

$$\begin{aligned} & \inf_{b(t) \leq u \leq x} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \\ & \geq rK - \delta x - \int (P(t, xe^y) - (K - xe^y)) \nu(dy) + o(\sqrt{\theta}) \\ & \geq b(T) - x \left( \delta + \int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \nu(dy) + \epsilon(\theta) \right) - K\nu \left\{ \ln \frac{K}{b(T)} \right\} \mathbb{E} \left( \sigma B_\theta - \ln \left( \frac{b(T)}{x} \right) \right)^+ + o(\sqrt{\theta}). \end{aligned}$$

We note  $\alpha = \frac{\nu\{\ln(\frac{K}{b(T)})\}}{\hat{\delta}} \frac{K}{b(T)}$  and  $\hat{\delta} = \delta + \int_{\{y > \ln(\frac{K}{b(T)})\}} e^y \nu(dy)$ ; we then have for all  $u$  and all  $x$  such that  $b(t) \leq u \leq x < b(T)$

$$\begin{aligned} & \inf_{b(t) \leq u \leq x} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u) \\ & \geq b(T) \hat{\delta} \left( \frac{(b(T) - x)}{b(T)} - \alpha \mathbb{E} \left( \sigma B_\theta - \ln \left( \frac{b(T)}{x} \right) \right)^+ \right) - (b(T) - x) \epsilon(\theta) + o(\sqrt{\theta}). \quad \blacksquare \end{aligned}$$

**Remark 2.** The expression  $\inf_{b(t) < u < x} \frac{u^2 \sigma^2}{2} \frac{\partial^2 P}{\partial x^2}(t, u)$  is justified thanks to the smoothness of  $P$  in the continuation region which can be proved thanks to PDE arguments (see, for instance [2]). Nevertheless, we will only need this lower bound of the second derivative in the distribution sense  $(\frac{\partial^2 P}{\partial x^2}(t, du))$ .

**Appendix B. A study of  $v_{\lambda, \beta}$ .**

**Lemma 4.1.** *There exists  $y_{\lambda, \beta} \in (0, (1 + \lambda\beta(2 + e^\lambda)))$  such that such that*

$$\begin{aligned} \forall y < -y_{\lambda, \beta}, \quad v_{\lambda, \beta}(y) &= 0, \\ y_{\lambda, \beta} &= - \inf \{x \in \mathbb{R} \mid v_{\lambda, \beta}(x) > 0\}. \end{aligned}$$

*Proof of Lemma 4.1.* We have

$$v_{\lambda, \beta}(y) = \sup_{\tau \in \mathcal{T}_{0,1}} (I_0(\tau) + I_1(\tau))$$

with

$$I_0(\tau) = \mathbb{E} \left( e^{\lambda \tau} 1_{\{\hat{N}_\tau = 0\}} \int_0^\tau f_{\lambda, \beta}(y + B_s) ds \right)$$

and

$$I_1(\tau) = \beta \mathbb{E} \left( e^{\lambda \tau} 1_{\{\hat{N}_\tau=1\}} \left( (y + B_\tau)^+ - (y + B_{\hat{T}_1})^+ \right) \right).$$

We will study  $I_0(\tau)$  and  $I_1(\tau)$ . First of all, we note that the process  $(M_t^0)_{t \geq 0}$  defined by  $M_t^0 = e^{\lambda t} 1_{\{\hat{N}_t=0\}}$  is a nonnegative martingale with  $M_0^0 = 1$ . Under the probability  $\mathbb{P}^0$  with density  $M_t^0$  on  $\mathcal{F}_t$ , it is straightforward to check that  $(B)_{t \geq 0}$  remains an  $\mathbb{F}$ -Brownian motion. We have, if  $y \leq 0$ ,

$$\begin{aligned} I_0(\tau) &= \mathbb{E}^0 \left( \int_0^\tau f_{\lambda\beta}(y + B_s) ds \right) \\ &= \mathbb{E}^0 \left( y\tau + \int_0^\tau B_s ds + \lambda\beta \int_0^\tau (y + B_s)^+ ds \right) \\ &\leq y\mathbb{E}^0(\tau) + (1 + \lambda\beta)\mathbb{E}^0 \left( \int_0^\tau B_s^+ ds \right) \\ &\leq y\mathbb{E}^0(\tau) + (\lambda\beta + 1)\mathbb{E}^0 \left( \int_0^\tau \mathbb{E}^0(B_\tau^+ | \mathcal{F}_s) ds \right). \end{aligned}$$

Notice that, for  $\tau \in \mathcal{T}_{0,1}$ ,

$$\begin{aligned} \mathbb{E}^0 \left( \int_0^\tau \mathbb{E}^0(B_\tau^+ | \mathcal{F}_s) ds \right) &= \mathbb{E}^0 \left( \int_0^1 1_{\{\tau > s\}} \mathbb{E}^0(B_\tau^+ | \mathcal{F}_s) ds \right) \\ &= \int_0^1 \mathbb{E}^0(1_{\{\tau > s\}} \mathbb{E}^0(B_\tau^+ | \mathcal{F}_s)) ds \\ &= \mathbb{E}^0(\tau B_\tau^+) \\ &\leq \mathbb{E}^0 \left( \frac{\tau^2 + B_\tau^2}{2} \right) \leq \mathbb{E}^0(\tau), \end{aligned}$$

where we used  $0 \leq \tau \leq 1$  for the last inequality. We then have

$$I_0(\tau) \leq (y + \lambda\beta + 1)\mathbb{E}^0(\tau).$$

For the study of  $I_1(\tau)$ , let us introduce the martingale  $(M_t^1)_{0 \leq t \leq 1}$  defined by

$$\begin{aligned} M_t^1 &= \mathbb{E} \left( e^{\lambda t} 1_{\{\hat{N}_t=1\}} | \mathcal{F}_t \right) \\ &= \mathbb{E} \left( e^{\lambda t} 1_{\{\hat{N}_t=1, \hat{N}_t=0\}} | \mathcal{F}_t \right) + \mathbb{E} \left( e^{\lambda t} 1_{\{\hat{N}_t=1, \hat{N}_t=1\}} | \mathcal{F}_t \right) \\ &= 1_{\{\hat{N}_t=0\}} e^{\lambda t} \mathbb{P}(\hat{N}_1 - \hat{N}_t = 1) + 1_{\{\hat{N}_t=1\}} e^{\lambda t} \mathbb{P}(\hat{N}_1 - \hat{N}_t = 0) \\ &= 1_{\{\hat{N}_t=0\}} \lambda(1-t)e^{\lambda t} + 1_{\{\hat{N}_t=1\}} e^{\lambda t}. \end{aligned}$$

Under the probability  $\mathbb{P}^1$  with density  $M_t^1/\lambda$  on  $\mathcal{F}_t$ , it is straightforward to check that  $(B_t)_{0 \leq t \leq 1}$  remains an  $\mathbb{F}$ -Brownian motion. We have for  $y < 0$

$$\begin{aligned} I_1(\tau) &= \lambda\beta \mathbb{E}^1 \left( (y + B_\tau)^+ - (y + B_{\hat{T}_1 \wedge \tau})^+ \right) \\ &\leq \lambda\beta \mathbb{E}^1 \left( (y + B_\tau)^+ \right) \\ &\leq \lambda\beta \mathbb{E}^1 \left( B_\tau 1_{\{B_\tau > -y\}} \right) \\ &\leq \lambda\beta \mathbb{E}^1 \left( B_\tau^2 / |y| \right) = \lambda\beta \mathbb{E}^1(\tau) / |y| \end{aligned}$$

Using the two upper bound of  $I_0(\tau)$  and  $I_1(\tau)$ , we obtain

$$\begin{aligned}
v_{\lambda,\beta}(y) &\leq \sup_{\tau \in \mathcal{T}_{0,1}} \left( (y + \lambda\beta + 1)\mathbb{E}^0(\tau) + \frac{\lambda\beta}{|y|}\mathbb{E}^1(\tau) \right) \\
&= \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left( (y + \lambda\beta + 1)\tau M^0(\tau) + \frac{\beta}{|y|}\tau M^1(\tau) \right) \\
&= \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left( (y + \lambda\beta + 1)\tau e^{\lambda\tau} 1_{\{\hat{N}_\tau=0\}} + \frac{\beta}{|y|}\tau \left( 1_{\{\hat{N}_\tau=0\}}\lambda(1-\tau)e^{\lambda\tau} + 1_{\{\hat{N}_\tau=1\}}e^{\lambda\tau} \right) \right) \\
&\leq \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left( f(\tau, \hat{N}_\tau) \right)
\end{aligned}$$

with

$$f(t, x) = 1_{\{x=0\}}te^{\lambda t} \left( y + 1 + \lambda\beta \left( 1 + \frac{1}{|y|} \right) \right) + 1_{\{x=1\}}\beta te^{\lambda t}/|y|.$$

Notice that

$$\sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \left( f(\tau, \hat{N}_\tau) \right) = \sup_{\tau \in \mathcal{T}_{0,1}(\hat{N})} \mathbb{E} \left( f(\tau, \hat{N}_\tau) \right),$$

where  $\mathcal{T}_{0,1}(\hat{N})$  denotes the set of the stopping times of the natural completed filtration of the process  $(\hat{N}_t)_{t \geq 0}$ , with values in  $[0, 1]$ .

Then, if  $\tau \in \mathcal{T}_{0,1}(\hat{N})$ , there exists, thanks to Lemma B.1,  $t_0 \in [0, 1]$  such that

$$\tau \wedge \hat{T}_1 = t_0 \wedge \hat{T}_1.$$

We then have

$$\begin{aligned}
\mathbb{E} \left( \tau e^{\lambda\tau} 1_{\{\hat{N}_\tau=0\}} \right) &= \mathbb{E} \left( \tau e^{\lambda\tau} 1_{\{\hat{T}_1 > \tau\}} \right) \\
&= t_0 e^{\lambda t_0} \mathbb{P}(\hat{T}_1 > \tau) \\
&= t_0
\end{aligned}$$

and

$$\begin{aligned}
\mathbb{E} \left( \tau e^{\lambda\tau} 1_{\{\hat{N}_\tau=1\}} \right) &\leq \mathbb{E} \left( \tau e^{\lambda\tau} 1_{\{\hat{T}_1 \leq \tau\}} \right) \\
&= \mathbb{E} \left( \tau e^{\lambda\tau} 1_{\{\hat{T}_1 \leq t_0\}} \right) \\
&\leq e^{\lambda} \mathbb{P}(\hat{T}_1 \leq t_0) \\
&= e^{\lambda}(1 - e^{-\lambda t_0}) \leq \lambda e^{\lambda} t_0.
\end{aligned}$$

We deduce that

$$\sup_{\tau \in \mathcal{T}_{0,1}(\hat{N})} \mathbb{E} \left( f(\tau, \hat{N}_\tau) \right) \leq \sup_{0 \leq t_0 \leq 1} \left( t_0 \left( y + 1 + \lambda \frac{\beta(2 + e^\lambda)}{|y|} \right) \right).$$

The right-hand side of this equation will be equal to 0 if

$$y + 1 + \lambda \frac{\beta(2 + e^\lambda)}{|y|} \leq 0,$$

and particularly, if  $y \leq -(1 + \lambda\beta(2 + e^\lambda))$ , then

$$-y_{\lambda,\beta} \geq -(1 + \lambda\beta(2 + e^\lambda)).$$

To prove  $-y_{\lambda,\beta} < 0$ , we consider  $y = 0$ . Since for all stopping time  $\tau$ ,

$$\mathbb{E} \left( e^{\lambda\tau} 1_{\{\hat{N}_\tau=0\}} \int_0^\tau \lambda\beta(y + B_s)^+ ds + \beta e^{\lambda\tau} 1_{\{\hat{N}_\tau=1\}} \left( (y + B_\tau)^+ - (y + B_{\hat{T}_1})^+ \right) \right) \geq 0,$$

we have

$$v_{\lambda,\beta}(0) \geq \sup_{\tau \in \mathcal{T}_{0,1}} \mathbb{E} \int_0^\tau B_s ds = v_0(0),$$

and it is proved in [14] or [4, Proposition 2.2.4],  $v_0(0) > 0$ . ■

**Lemma B.1.** *Let  $N = (N_t)_{t \geq 0}$  a homogeneous Poisson process with intensity  $\lambda$  and  $T_1$  its first jump time. If  $\tau$  is a stopping time of the natural completed filtration of  $N$  such that  $\tau \leq T_1$  a.s., then  $\tau = T_1$  a.s., or there exists  $t_0 \geq 0$ , such that  $\tau = t_0 \wedge T_1$  a.s.*

*Proof.* We denote by  $\mathbb{F} = (\mathcal{F}_t)_{t \geq 0}$  the natural completed filtration of  $N$ . First of all, notice that for all  $t \geq 0$  and  $A \in \mathcal{F}_t$ ,

$$\mathbb{P}(A \mid N_t = 0) \in \{0, 1\}.$$

Indeed, the  $A$  having this property form a sub  $\sigma$ -algebra of  $\mathcal{F}_t$  which contains the events of the form  $\{N_s = n\}$ , with  $0 \leq s \leq t$  and  $n \in \mathbb{N}$ .

Now, let  $\tau$  be a  $\mathbb{F}$ -stopping time. We have for all  $t \geq 0$ ,  $\mathbb{P}(\tau > t \mid N_t = 0) \in \{0, 1\}$ . We set

$$I = \{t \in [0, +\infty[ \mid \mathbb{P}(\tau > t \mid N_t = 0) = 0\}.$$

Notice that  $t \in I$  if and only if  $\mathbb{P}(\tau > t, T_1 > t) = 0$ , or

$$t \in I \Leftrightarrow \mathbb{P}(\tau \wedge T_1 \leq t) = 1.$$

If  $\tau \leq T_1$  a.s. and if  $\mathbb{P}(\tau < T_1) > 0$ , there exists  $s > 0$  (rational number) such that  $\mathbb{P}(\tau \leq s, s < T_1) > 0$ , hence  $\mathbb{P}(\tau \leq s \mid N_s = 0) > 0$ , and  $\mathbb{P}(\tau > s \mid N_s = 0) = 0$ . We deduce that  $I$  is nonempty and we can write

$$I = [t_0, +\infty[, \text{ with } t_0 = \inf\{t \geq 0 \mid \mathbb{P}(\tau > t \mid N_t = 0) = 0\}.$$

We then have  $\tau \wedge T_1 \leq t_0$  a.s., hence  $\tau \leq t_0 \wedge T_1$ . Moreover, for  $s < t_0$ , we have  $\mathbb{P}(\tau > s \mid N_s = 0) = 1$  and  $\mathbb{P}(\tau \leq s \mid N_s = 0) = 0$ , hence  $\mathbb{P}(\tau \leq s, s < T_1) = 0$ . Therefore,  $\mathbb{P}(\tau < t_0 \wedge T_1) = 0$  and consequently  $\tau = t_0 \wedge T_1$  a.s. ■

**LEMMA 4.2.** *For all  $x > y_{\lambda,\beta}$ , we have*

$$C(x) > 0.$$

*Proof.* We have  $v_{\lambda,\beta}(-y_{\lambda,\beta}) = 0$ ; considering the stopping time  $\tau = 1$ , we obtain

$$\mathbb{E} \left[ e^{\lambda 1} 1_{\{\hat{N}_1=0\}} \int_0^1 f_{\lambda\beta}(B_s - y_{\lambda,\beta}) ds + \beta e^{\lambda 1} 1_{\{\hat{N}_1=1\}} \left( (B_1 - y_{\lambda,\beta})^+ - (B_{\hat{T}_1} - y_{\lambda,\beta})^+ \right) \right] \leq 0.$$

However, we have, using the independence between  $\hat{N}$  and  $B$ ,

$$\begin{aligned} \mathbb{E} \left[ e^{\lambda} \mathbf{1}_{\{\hat{N}_1=0\}} \int_0^1 f_{\lambda\beta}(B_s - y_{\lambda,\beta}) ds \right] &= e^{\lambda} \mathbb{P}(\hat{N}_1 = 0) \left( -y_{\lambda,\beta} + \lambda\beta \mathbb{E} \int_0^1 (B_s - y_{\lambda,\beta})^+ ds \right) \\ (34) \qquad \qquad \qquad &= -y_{\lambda,\beta} + \lambda\beta \mathbb{E} \int_0^1 (B_s - y_{\lambda,\beta})^+ ds. \end{aligned}$$

On the other hand, we have

$$\begin{aligned} &\mathbb{E} \left[ \beta e^{\lambda} \mathbf{1}_{\{\hat{N}_1=1\}} \left( (B_1 - y_{\lambda,\beta})^+ - (B_{\hat{T}_1} - y_{\lambda,\beta})^+ \right) \right] \\ &= \beta e^{\lambda} \mathbb{P}(\hat{N}_1 = 1) \left[ \mathbb{E}(B_1 - y_{\lambda,\beta})^+ - \mathbb{E} \left( (B_{\hat{T}_1} - y_{\lambda,\beta})^+ | \hat{N}_1 = 1 \right) \right] \\ &= \beta \lambda \left[ \mathbb{E}(B_1 - y_{\lambda,\beta})^+ - \mathbb{E} \left( (B_{\hat{T}_1} - y_{\lambda,\beta})^+ | \hat{T}_1 \leq 1 \right) \right]. \end{aligned}$$

Noticing that  $\lambda\beta = \lambda\beta$  and that conditionally to  $\{\hat{T}_1 \leq 1\}$ ,  $\hat{T}_1$  is uniformly distributed on  $[0, 1]$ , we obtain

$$\begin{aligned} &\mathbb{E} \left[ \beta e^{\lambda} \mathbf{1}_{\{\hat{N}_1=1\}} \left( (B_1 - y_{\lambda,\beta})^+ - (B_{\hat{T}_1} - y_{\lambda,\beta})^+ \right) \right] \\ (35) \qquad \qquad \qquad &= \lambda\beta \left[ \mathbb{E}(B_1 - y_{\lambda,\beta})^+ - \mathbb{E} \left( \int_0^1 (B_s - y_{\lambda,\beta})^+ ds \right) \right]. \end{aligned}$$

Combining (34) and (35), we have

$$-y_{\lambda,\beta} + \lambda\beta \mathbb{E}(B_1 - y_{\lambda,\beta})^+ = -C(y_{\lambda,\beta}) \leq 0.$$

To conclude the proof, we use the strict increasing of  $C$ , and hence for all  $x > y_{\lambda,\beta}$ , we have

$$C(x) > C(y_{\lambda,\beta}) \geq 0. \quad \blacksquare$$

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