

Johann Radon Institute for Computational and Applied Mathematics Austrian Academy of Sciences (ÖAW)



# Dividend maximization under consideration of the time value of ruin

H. Albrecher, S. Thonhauser

RICAM-Report 2006-20

### DIVIDEND MAXIMIZATION UNDER CONSIDERATION OF THE TIME VALUE OF RUIN\*

STEFAN THONHAUSER<sup>a</sup> HANSJÖRG ALBRECHER<sup>a, b</sup>

<sup>a</sup> Radon Institute for Computational and Applied Mathematics, Austrian Academy of Sciences, Altenbergerstrasse 69, A-4040 Linz, Austria

<sup>b</sup> Graz University of Technology, Steyrergasse 30, A-8010 Graz, Austria

### Abstract

In the Cramér-Lundberg model and its diffusion approximation, it is a classical problem to find the optimal dividend payment strategy that maximizes the expected value of the discounted dividend payments until ruin. One often raised disadvantage of this approach is the fact that such a strategy does not take the life time of the controlled process into account. In this paper we introduce a value function which considers both expected dividends and the time value of ruin. For both the diffusion model and the Cramér-Lundberg model with exponential claim sizes, the problem is solved and in either case the optimal strategy is identified, which for unbounded dividend intensity is a barrier strategy and for bounded dividend intensity is of threshold type.

# 1 Introduction

The classical optimal dividend problem looks for the strategy that maximizes the expected discounted dividend payments until ruin in an insurance portfolio. For the compound Poisson model, this problem was solved by Gerber [9], identifying so-called *band strategies* as the optimal ones. For exponentially distributed claim sizes this strategy simplifies to a *barrier strategy*, i.e. whenever the surplus exceeds some barrier level b, all the income is paid out as dividends and no dividends are paid out below that surplus level. In [9], the result is first obtained for a discrete version of the model and then obtained for the continuous model by a limiting procedure. Recently, the optimal dividend problem in the compound Poisson model was taken up again by Azcue and Muler [2], who used stochastic optimal control techniques and viscosity solutions.

The corresponding problem in the case of a diffusion risk process was solved in Asmussen & Taksar [1]. Taksar [23] gives an extensive picture over the above and related maximisation problems, where also additional possibilities of control such as reinsurance are treated. Gerber & Shiu [11] showed that in case the admissible dividend payment intensity is bounded above by some constant M < c (where c is the premium intensity of the surplus process), for exponential claim sizes a so-called *threshold strategy* maximizes the expected discounted dividend payments (i.e. whenever the surplus is below a certain threshold, no dividends are paid out and above that level the maximal allowed amount is paid). In a diffusion setting, a corresponding result was already established in [1].

However, all the strategies outlined above lead to ruin with probability one and in many circumstances this is not desirable. On the other hand, there has also been a lot of research activity on using optimal control to minimize the ruin probability. For instance, for the diffusion approximation, Browne [5] considered the case where the insurer is allowed to invest in a risky asset which follows a geometric Brownian motion and identified the optimal investment strategy that minimizes the ruin probability of the resulting risk process. For extensions to the Cramér-Lundberg model, see e.g. Hipp & Plum [13], Gaier & Grandits [8]. The problem of choosing optimal dynamic proportional reinsurance to minimize ruin probabilities was investigated by Schmidli [19] and optimal excess-of-loss reinsurance strategies were considered in Hipp & Vogt [14]. Combinations of both investment and reinsurance are considered in Schmidli [20], see Schmidli [22] for a nice recent survey on this subject.

<sup>\*</sup>Supported by the Austrian Science Fund Project P-18392.

In this paper we return to the problem of optimal dividend payments, but add a component to the objective function that penalizes early ruin of the controlled risk process. In particular, this additional term can be interpreted as a continuous payment of a (discounted) constant intensity during the lifetime of the controlled process. It will turn out that this choice of objective function leads to a particularly tractable extension of the corresponding available results for pure dividend maximization (in particular Asmussen & Taksar [1] and Hojgaard & Taksar [15]), and hence considerable parts of the proofs are along the lines of the above papers, however keeping track of the consequences of the additional term in the objective function. The approach should be seen as a first tractable step towards more refined optimization criteria in the corresponding optimal control problems.

The paper is organized as follows. In Section 2, the Cramér-Lundberg model and its diffusion approximation are shortly discussed and the value function underlying our approach is introduced. Section 3 deals with the case of a diffusion risk process and the optimal control problem is solved explicitly, both for bounded and unbounded dividend intensity and the effect of the time value of ruin on the optimal strategy is investigated. It is also shown that if in addition to dividend payouts there is a possibility for dynamic proportional reinsurance, then the optimal strategy from Hojgaard & Taksar [15] is also optimal in our case, just adding a constant term in the value function. Section 4 deals with the above optimal control problem for the classical Cramér-Lundberg process. For exponential claim amounts the explicit solution is obtained, which extends the results of Gerber [9] and Gerber & Shiu [11] for unbounded and bounded dividend intensity, respectively. In each section numerical examples are given that illustrate the modification of the optimal strategy with the additional term in the objective function.

After this manuscript was finished, the authors found an unpublished manuscript of Boguslavskaya [4], who in a financial context used a similar objective function in the diffusion setting and solved it using the theory of free boundary problems. However, the approach in Section 3 provides a somewhat more intuitive way of proof, using classical stochastic optimal control techniques, which also allows us to extend the results to the Cramér-Lundberg model in Section 4.

Finally, we would like to point out that in a recent paper, Gerber et al. [10] conjecture that in case of unbounded dividend intensity, horizontal barrier strategies are optimal for the maximization of the difference of the expected discounted dividends and the deficit at ruin. The results in this paper establish optimality of horizontal barrier strategies for the inclusion of another safety criterion, namely the life-time of the controlled risk process.

# 2 Model and Value function

Let  $(\Omega, \mathcal{F}, P)$  be an underlying complete probability space with a filtration  $(\mathcal{F}_t)_{t\geq 0}$  that models the flow of information. Let  $W = (W_t)_{t\geq 0}$  be a standard Brownian motion with respect to the given filtration. In this paper two models for the collective risk process are considered. In a first approach the risk process  $R = (R_t)_{t\geq 0}$  is described by a diffusion process. Apart from the fact that this assumption simplifies the analysis and leads to structural results, it can also be motivated by an approximation argument towards a compound Poisson model (see [12], [16], [21] or [3]). We denote the drift term by  $\mu > 0$  and the standard deviation by  $\sigma$ , then the process with initial capital x is defined via

$$dR_t = \mu dt + \sigma dW_t, \quad R_0 = x.$$

Alternatively, we will also work in the Cramér-Lundberg model, where the risk reserve process  $R = (R_t)_{t\geq 0}$  with initial capital x is defined by

$$R_t = x + ct - \sum_{i=0}^{N_t} Y_i, \quad t \ge 0.$$
 (1)

Here c > 0 is the constant premium intensity and the claim amounts are an independent and identically distributed sequence  $\{Y_i\}_{i \in \mathbb{N}}$  of positive random variables with distribution function  $F_Y(y)$ . The claim number process  $N = (N_t)_{t \geq 0}$  is assumed to be Poisson with intensity  $\lambda > 0$ , which is independent of  $\{Y_i\}_{i \in \mathbb{N}}$ .

In the following the insurer is allowed to pay dividends. The cumulated dividends are described by a process  $L = (L_t)_{t \ge 0}$ , which is called *admissible*, if it is a positive increasing càdlàg process, adapted to  $(\mathcal{F}_t)_{t \ge 0}$ .  $L_t$  represents the total dividends up to time t and the resulting controlled risk process is given by

$$R_t^L = R_t - L_t.$$

The time of ruin for this process is defined by  $\tau := \tau^L = \inf\{t \ge 0 \mid R_t^L < 0\}$ . Let furthermore  $\tau' = \inf\{t \ge 0 \mid R_t^L = 0\}$ , then for a pure diffusion process  $\tau = \tau'$ . We can write

$$L_t = \int_0^t e^{-\beta s} l_s \, ds,$$

where  $(l_s)_{s\geq 0}$  is the dividend intensity. Furthermore we require that paying dividends can not cause ruin,  $L_t - L_{t-} \leq R_t^L$  and also  $L_{0-} = 0$ . Moreover no dividends can be paid after ruin, i.e.  $L_t = L_{\tau}$  for all  $t > \tau$ .

In this paper we aim to identify the dividend payment strategy  $L = (L_t)_{t \ge 0}$  that maximizes

$$V(x,L) = \mathbb{E}\left(\int_0^\tau e^{-\beta t} dL_t + \int_0^\tau e^{-\beta t} \Lambda dt \mid R_0^L = x\right)$$
(2)

for some  $\Lambda > 0$ , i.e. we are looking for the value function

$$V(x) = \sup_{L} V(x, L), \tag{3}$$

where the supremum is taken over all admissible strategies.

Note that compared to the classical value function, which maximizes the expected discounted dividend payments, there is an additional term depending on the time of ruin.  $e^{-\beta t} \Lambda$  can be interpreted as the present value of an amount which the insurer earns as long as the company is alive. In this way the lifetime of the portfolio becomes part of the value function and is weighted according to the choice of  $\Lambda$ . Another interpretation is that in this way the Laplace transform of the ruin time is part of the value function.

# 3 Optimal strategy for the diffusion case

Let us distinguish the two cases of bounded and unbounded dividend intensity  $l_s$ .

## 3.1 Bounded Dividend Intensity

Let  $0 \leq l_t \leq M$  for  $t \geq 0$ . Then the value function (3) is given by

$$V(x) = \sup_{0 \le l \le M} \mathbb{E} \left( \int_0^\tau e^{-\beta t} \left( l_t + \Lambda \right) dt \mid R_0^L = x \right),$$
  
$$V(0) = 0.$$

Clearly V(x) is bounded by  $(M + \Lambda)/\beta$ . Standard arguments, see [7], formally yield the Hamilton-Jacobi-Bellman (HJB) equation

$$0 = -\beta V(x) + \sup_{0 \le l \le M} \left\{ (\mu - l) V'(x) + \frac{\sigma^2}{2} V''(x) + l + \Lambda \right\},$$

which can be rewritten as

$$0 = -\beta V(x) + \mu V'(x) + \frac{\sigma^2}{2} V''(x) + \Lambda + \sup_{0 \le l \le M} \left\{ (1 - V'(x))l \right\}.$$
 (4)

Let us first assume that V is a strictly concave function, V' > 0 and V'' < 0. Then there exists some point  $x_0$  with the following properties:

$$x < x_0:$$
  $V'(x) > 1,$   
 $x \ge x_0:$   $V'(x) \le 1.$ 

In the sequel it will be seen that this working assumption indeed leads to the optimal strategy. Based on the linearity of the control l in (4) we get that the optimal control  $l^*(x)$  has to fulfill

$$l^*(x) = \begin{cases} 0 & x < x_0, \\ M & x \ge x_0. \end{cases}$$

Therefore (4) translates into

$$0 = -\beta V(x) + \mu V'(x) + \frac{\sigma^2}{2} V''(x) + \Lambda, \quad x < x_0,$$
(5)

$$0 = -\beta V(x) + (\mu - M)V'(x) + \frac{\sigma^2}{2}V''(x) + \Lambda + M, \quad x \ge x_0,$$

$$0 = V(0),$$
(6)

and the crucial point  $x_0$  has to be determined by the method of *smooth fit*. Let  $V_l$  denote the solution of (5) and  $V_r$  the solution of (6). Since in (5) and (6) there are derivatives of the value function up to order 2, we have to look for a twice differentiable solution. This leads to the following pasting conditions at  $x_0$ :

$$V_l(x_0) = V_r(x_0),$$
 (7)

$$V_{l}'(x_{0}) = V_{r}'(x_{0}) = 1,$$

$$V_{l}''(x_{0}) = V_{l}''(x_{0}) = 0$$
(8)
$$V_{l}''(x_{0}) = V_{l}''(x_{0}) = 0$$
(9)

$$V_l''(x_0) = V_r''(x_0), (9)$$

A general solution of (5) is of the form

$$V_l(x) = \frac{\Lambda}{\beta} + A_1 \ e^{R_1 x} + A_2 \ e^{R_2 x},$$

with

$$R_{1,2} = -\frac{\mu}{\sigma^2} + \sqrt{\frac{\mu^2}{\sigma^4} + \frac{2\beta}{\sigma^2}}.$$

Note that  $R_1 > 0$  and  $R_2 < 0$ . The condition V(0) = 0 gives  $A_2 = -(\Lambda/\beta + A_1)$ . Similarly,

$$V_r(x) = \frac{M + \Lambda}{\beta} + B_1 \ e^{S_1 x} + B_2 \ e^{S_2 x},$$

with

$$S_{1,2} = -\frac{(\mu - M)}{\sigma^2} + \sqrt{\frac{(\mu - M)^2}{\sigma^4} + \frac{2\beta}{\sigma^2}}.$$

From the boundedness of the value function we know that if any of the exponents is positive, the corresponding coefficient has to be zero. Hence, from  $S_1 > 0$ ,

$$V_r(x) = \frac{M + \Lambda}{\beta} + B_2 \ e^{S_2 x},$$

where  $B_2 < 0$  is a constant. Now we use (7)-(9) to determine  $x_0$  and the remaining coefficients  $A_1$  and  $B_2$  (which are functions of  $x_0$ ). We have

$$\frac{\Lambda}{\beta} + A_1 e^{R_1 x_0} - (A_1 + \frac{\Lambda}{\beta}) e^{R_2 x_0} = \frac{M + \Lambda}{\beta} + B_2 e^{S_2 x_0},$$
(10)

$$A_1 R_1 e^{R_1 x_0} - (A_1 + \frac{\Lambda}{\beta}) R_2 e^{R_2 x_0} = B_2 S_2 e^{S_2 x_0} = 1,$$
(11)

$$A_1 R_1^2 e^{R_1 x_0} - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2^2 e^{R_2 x_0} = B_2 S_2^2 e^{S_2 x_0}.$$
(12)

If we use the right equality of (11) in (10), we get with  $\delta(M) := M/\beta + 1/S_2$ 

$$x_0 = \frac{1}{R_1 - R_2} \log \left( \frac{A_1(x_0) + \frac{\Lambda}{\beta}}{A_1(x_0)} \frac{1 - \delta(M) R_2}{1 - \delta(M) R_1} \right).$$
(13)

and correspondingly from (11)

$$B_2 = \frac{1}{S_2} \left( \frac{A_1(x_0) + \frac{\Lambda}{\beta}}{A_1(x_0)} \frac{1 - \delta(M) R_2}{1 - \delta(M) R_1} \right)^{\frac{-S_2}{R_1 - R_2}}.$$
 (14)

After substitution of (13) in (11),  $A_1$  is obtained as a solution of a nonlinear equation, see (15) below. Lemma 1. For all M > 0

$$\frac{1}{R_2} < \delta(M) < \frac{1}{R_1}$$

Proof. From

$$\frac{1}{R_1} - \delta = \frac{1}{2\beta} \left( -M + \sqrt{\mu^2 + 2\beta\sigma^2} + \sqrt{(\mu - M)^2 + 2\beta\sigma^2} \right)$$

the right inequality holds if

$$\sqrt{\mu^2 + 2\beta\sigma^2} > M - \sqrt{(\mu - M)^2 + 2\beta\sigma^2} := G(M).$$

Indeed, since

$$G'(M) = 1 - \frac{M-\mu}{\sqrt{(\mu-M)^2 + 2\beta\sigma^2}} > 0$$

and

$$\lim_{M \to \infty} G(M) = \lim_{M \to \infty} \frac{M^2 - M^2 + 2M\mu - \mu^2 - 2\beta\sigma^2}{M + \sqrt{M^2 - 2M\mu + \mu^2 + 2\beta\sigma^2}} = \lim_{M \to \infty} \frac{2\mu - \frac{\mu^2 + 2\beta\sigma^2}{M}}{1 + \sqrt{1 - \frac{2\mu}{M} + \frac{\mu^2 + 2\beta\sigma^2}{M^2}}} = \mu,$$

G(M) is a monotone increasing function with  $\lim_{M\to\infty} G(M) = \mu < \sqrt{\mu^2 + 2\beta\sigma^2}$ . The second inequality follows from

$$\delta - \frac{1}{R_2} = \frac{M\left(1 - \frac{M - 2\mu}{\sqrt{(\mu - M)^2 + 2\beta\sigma^2} + \sqrt{\mu^2 + 2\beta\sigma^2}}\right)}{2\beta}$$

and the fact that  $\sqrt{(\mu - M)^2 + 2\beta\sigma^2} > M - \mu$  and  $\sqrt{\mu^2 + 2\beta\sigma^2} > \mu > 0$ . Define

$$F(H) := \frac{1 + \frac{\Lambda}{\beta} R_2 \left(\frac{H + \frac{\Lambda}{\beta}}{H} \frac{1 - \delta R_2}{1 - \delta R_1}\right)^{\frac{R_1}{R_1 - R_2}}}{R_1 \left(\frac{H + \frac{\Lambda}{\beta}}{H} \frac{1 - \delta R_2}{1 - \delta R_1}\right)^{\frac{R_1}{R_1 - R_2}} - R_2 \left(\frac{H + \frac{\Lambda}{\beta}}{H} \frac{1 - \delta R_2}{1 - \delta R_1}\right)^{\frac{R_2}{R_1 - R_2}} - H.$$
(15)

Note that the denominator of (15) is strictly positive.

**Lemma 2.** If  $\frac{M+\Lambda}{\beta} + \frac{1}{S_2} \leq 0$  then

$$V^*(x) = \frac{M + \Lambda}{\beta} \left( 1 - e^{S_2 x} \right)$$

is a twice continuously differentiable strictly concave solution of the HJB equation (4). If  $\frac{M+\Lambda}{\beta} + \frac{1}{S_2} > 0$ , then  $x_0 > 0$  and

$$V^*(x) = \begin{cases} \frac{\Lambda}{\beta} + A_1 \ e^{R_1 x} - (A_1 + \frac{\Lambda}{\beta}) \ e^{R_2 x} & x < x_0, \\ \frac{M + \Lambda}{\beta} - C_2 \ e^{S_2 x} & x \ge x_0, \end{cases}$$

is a twice differentiable strictly concave solution of the HJB equation (4). The coefficient  $B_2$  and  $x_0$  are calculated from (14) and (13), while  $A_1$  is a positive root of F(H) as defined in (15).

*Proof.* First we look at the case  $\frac{M+\Lambda}{\beta} + \frac{1}{S_2} > 0$ . From Lemma 1 we know that  $1 - \delta R_2$  and  $1 - \delta R_1$  are positive. Hence we have to ensure  $\frac{A_1 + \frac{\Lambda}{\beta}}{A_1} > 0$ , as otherwise  $x_0$  in (13) is not a real number. This implies  $A_1 > 0$ , as the alternative  $A_1 < -\frac{\Lambda}{\beta}$  would lead to a decreasing function  $V^*(x)$  for  $x < x_0$ . So we are looking for a positive root  $A_1$  of F(H) as defined in (15), which can be rewritten as

$$F(H) = \frac{\frac{\Lambda}{\beta}R_2 + \left(\frac{H + \frac{\Lambda}{\beta}}{H}\frac{1 - \delta R_2}{1 - \delta R_1}\right)^{\frac{-R_2}{R_1 - R_2}}}{R_1 \left(\frac{H + \frac{\Lambda}{\beta}}{H}\frac{1 - \delta R_2}{1 - \delta R_1}\right) - R_2} - H.$$

From  $0 < \frac{-R_2}{R_1 - R_2} < 1$  we see that  $\lim_{H \to 0} F(H) = 0$  and  $\lim_{H \to \infty} F(H) = -\infty$ . Further we have for sufficiently small H > 0 that

$$\frac{\Lambda}{\beta}R_2 + \left(\frac{H + \frac{\Lambda}{\beta}}{H}\frac{1 - \delta R_2}{1 - \delta R_1}\right)^{\frac{-R_2}{R_1 - R_2}} > -R_2 H + R_1 \left(H + \frac{\Lambda}{\beta}\right) \left(\frac{1 - \delta R_2}{1 - \delta R_1}\right) > 0$$

The continuity of F(H) thus establishes the existence of a strictly positive root  $A_1$ , which is the desired coefficient. In view of (13),  $x_0 > 0$  if

$$\frac{A_1 + \frac{\Lambda}{\beta}}{A_1} \frac{1 - \delta R_2}{1 - \delta R_1} > 1$$

which is equivalent to

$$A_1\delta(R_1 - R_2) + \frac{\Lambda}{\beta}(1 - \delta R_2) > 0$$

which always holds for  $\delta \geq 0$ . For  $\delta = \frac{M}{\beta} + \frac{1}{S_2} < 0$  we need  $A_1 < -\frac{\Lambda}{\beta} \frac{1 - \delta R_2}{\delta(R_1 - R_2)}$ , which due to

$$F\left(-\frac{\Lambda}{\beta}\frac{1-\delta R_2}{\delta(R_1-R_2)}\right) = \frac{\beta+(M+\Lambda)S_2}{2(\beta+MS_2)\sqrt{\frac{\mu^2}{\sigma^4}+\frac{2\beta}{\sigma^2}}} < 0$$

is guaranteed under the assumption  $\frac{M+\Lambda}{\beta} + \frac{1}{S_2} > 0$ . So in this case indeed  $x_0 > 0$ .  $V^*(x)$  is clearly differentiable on  $\mathbb{R}^+$  and particularly in  $x_0$ . Because  $V_l$  solves (5) in  $x_0$  and  $V_r$  solves (6) in  $x_0$  we get by substitution of  $V_l(x_0) = V_r(x_0)$  and  $V'_l(x_0) = V'_r(x_0) = 1$  in (5) and (6) directly that  $V_l''(x_0) = V_r''(x_0)$  also holds.

Next we show that  $V^*(x)$  is strictly concave for  $x < x_0$ . Recall that  $A_1 > 0$  and  $A_1 + \frac{\Lambda}{\beta} > 0$ . We have

$$V^{*''}(x) = A_1 R_1^2 e^{R_1 x} - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2^2 e^{R_2 x},$$
  
$$V^{*'''}(x) = A_1 R_1^3 e^{R_1 x} - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2^3 e^{R_2 x} > 0,$$

so that  $V^{*''}$  is strictly increasing. From

$$V^{*''}(0) = A_1 R_1^2 - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2^2 < 0$$

and  $V^{*''}(x_0) = S_2 < 0$  we deduce that  $V^{*''}(x) < 0$  for all  $x \in [0, x_0]$ . Furthermore,  $V^{*'} > 0$  and therefore  $V^{*'}(x_0) = 1$  is a strict lower bound for the derivative in  $[0, x_0)$ . On the other hand, it is easy to see that for  $x \ge x_0$ 

$$V^{*'}(x) = B_2 S_2 e^{S_2 x} > 0,$$
  
$$V^{*''}(x) = B_2 S_2^2 e^{S_2 x} < 0,$$

and hence  $V^{*'}(x_0) = 1$  is a strict upper bound for  $V^{*'}(x)$  in  $(x_0, \infty)$ .

Finally, the case  $\frac{M+\Lambda}{\beta} + \frac{1}{S_2} < 0$  is verified by direct calculation. From  $S_2 < 0$  we have

$$V^{\ast'}(x) = -\frac{M+\Lambda}{\beta}S_2 \ e^{S_2 x} \le -\frac{M+\Lambda}{\beta}S_2 < 1$$

and  $V^{*'}(x) > 0$  for all  $x \ge 0$ . Furthermore

$$V^{*''}(x) = -\frac{M+\Lambda}{\beta}S_2^2 e^{S_2 x} \le 0$$

so that  $V^*(x)$  is indeed a strictly increasing concave function.

**Remark 1.** Equations (10), (11) and (13) generalize equations (2.19), (2.20), (2.21) and (2.26) from [1], where the case  $\Lambda = 0$  was treated. Note that in contrast to [1] the unknown  $x_0$  depends on the coefficient  $A_1$  and therefore the equation for  $A_1$  becomes nonlinear (whereas in [1, (2.26)] the independence of  $x_0$  and  $A_1$  led to linear equations). The height of the barrier  $x_0$  raises for increasing  $\Lambda$ , reflecting the reduced risk one is willing to take in case the lifetime of the controlled process is taken into account.

Finally we need a verification theorem proving that the value function obtained in Lemma 2 is indeed optimal:

**Proposition 3.** Let L be an admissible dividend strategy then for  $V^*(x)$  given in Lemma 2,  $V^*(x) \ge V(x,L)$  and  $V^*(x) = V(x,L^*)$ . The strategy  $L^*$  is given by

$$L_t^* = \int_0^t l_s^* \ e^{-\beta s} \ ds,$$

and

$$l^*(x) = \begin{cases} 0 & x < x_0 \\ M & x \ge x_0. \end{cases}$$

*Proof.* Let L be an admissible strategy with bounded intensity  $(l_t)_{t>0}$ . From the Itô-formula we obtain

$$e^{-\beta(T\wedge\tau)}V^{*}(R_{T\wedge\tau}^{L}) - V^{*}(x) = \int_{0}^{T\wedge\tau} \left(\frac{1}{2}\sigma^{2}V^{*''}(R_{t}^{L}) + (\mu - l_{t})V^{*'}(R_{t}^{L}) - \beta V^{*}(R_{t}^{L})\right)e^{-\beta t} dt + \int_{0}^{T\wedge\tau} e^{-\beta t}V^{*'}(R_{t}^{L})\sigma dW_{t}.$$
 (16)

We know that  $V^{*'}(x)$  is a monotone decreasing function and therefore bounded by  $V^{*'}(0)$ , so the stochastic integral in (16) is a square integrable martingale with expectation zero. From the HJB equation (4) we know that the integrand of the first integral is bounded by  $-(l_t + \Lambda) e^{-\beta t}$ , so we get

$$\mathbb{E}\left(e^{-\beta(T\wedge\tau)}V^*(R_{T\wedge\tau}^L) \mid R_0^L = x\right) + \mathbb{E}\left(\int_0^{T\wedge\tau} (l_t + \Lambda)e^{-\beta t} dt \mid R_0^L = x\right) \le V^*(x)$$
(17)

The integrand in the second expectation is bounded by  $(M + \Lambda)/\beta$  which is also a bound for  $V^*(x)$ . We let  $T \to \infty$  and use dominated convergence to get

$$\mathbb{E}\left(\int_0^\tau (l_t + \Lambda)e^{-\beta t} dt \mid R_0^L = x\right) = V(x, L) \le V^*(x).$$

If we use the strategy  $L^*$  we get equality in (17). The same bounds hold as before and therefore  $V(x, L^*) = V^*(x)$ .

Figure 1 depicts the optimal dividend payout as a function of initial capital x for various values of  $\Lambda$  and Figure 2 shows the optimal threshold level as a function of  $\Lambda$ .



Figure 1: Value function for  $\Lambda=0,0.08,0.2,0.8$ 



Figure 2: Barrier as function of  $\Lambda$ 

#### 3.2Unbounded Dividend Intensity

Here the cumulated dividends are not absolutely continuous and we have to use tools from singular *control* (see for instance [7]). The amount of dividends associated with an admissible dividend strategy  $L = (L_t)_{t \ge 0}$  is given by

$$V(x,L) = \mathbb{E}\left(\int_0^\tau e^{-\beta t} dL_t + \int_0^\tau e^{-\beta t} \Lambda dt \mid R_0^L = x\right)$$

The value function of the optimization problem is

$$V(x) = \sup_{L} V(x, L),$$

where the supremum is taken over all admissible strategies. The classical variational inequalities (see [7]) deliver the HJB equation of this problem, namely

$$0 = \max\left\{\mu V'(x) + \frac{\sigma^2}{2}V''(x) - \beta V(x) + \Lambda, 1 - V'(x)\right\},$$

$$0 = V(0).$$
(18)

At first we again assume that V(x) is strictly concave and that a crucial point  $x_0$  with V'(x) > 1 for  $x < x_0, V'(x_0) = 1$  and V'(x) < 1 for  $x > x_0$  exists ( $x_0$  will play the role of a classical dividend barrier). This gives

$$0 = \mu V'(x) + \frac{\sigma^2}{2} V''(x) - \beta V(x) + \Lambda, \quad x < x_0,$$

$$0 = 1 - V'(x), \quad x \ge x_0.$$
(19)
(20)

$$= 1 - V'(x), \quad x \ge x_0.$$
 (20)

As in the bounded case, due to the principle of *smooth fit*, the value function has to fulfill

$$V_l(x_0) = V_r(x_0),$$
 (21)

$$V_l'(x_0) = V_r'(x_0) = 1,$$
 (22)

$$V_l''(x_0) = V_r''(x_0) = 0, (23)$$

where again  $V_l(x)$  and  $V_r(x)$  denote the function V(x) for  $x < x_0$  and  $x \ge x_0$ , respectively. Hence

$$V_l(x) = \frac{\Lambda}{\beta} + A_1 e^{R_1 x} - \left(A_1 + \frac{\Lambda}{\beta}\right) e^{R_2 x},$$

with

$$R_{1,2} = -\frac{\mu}{\sigma^2} + \sqrt{\frac{\mu^2}{\sigma^4} + 2\frac{\beta}{\sigma^2}},$$

Note that  $R_2 < 0 < R_1$  with  $|R_2| > R_1$ . The solution for the right part  $x \ge x_0$  is a straight line given by  $V_r(x) = B_1 + x.$ 

In terms of these two functions the conditions (21)-(23) read as follows:

$$\frac{\Lambda}{\beta} + A_1 e^{R_1 x_0} - \left(A_1 + \frac{\Lambda}{\beta}\right) e^{R_2 x_0} = B_1 + x_0,$$

$$A_1 R_1 e^{R_1 x_0} - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2 e^{R_2 x_0} = 1,$$

$$A_1 R_1^2 e^{R_1 x_0} - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2^2 e^{R_2 x_0} = 0.$$
(24)

For  $x_0$  we get

$$x_0 = \frac{1}{R_1 - R_2} \log \left( \frac{A_1(x_0) + \frac{\Lambda}{\beta}}{A_1(x_0)} \frac{R_2^2}{R_1^2} \right).$$
(25)

The constant  $B_1$  is determined by  $B_1 = V_l(x_0) - x_0$  and the coefficient  $A_1$  is a root of the function

$$F(H) := H R_1 e^{R_1 x_0} - \left(H + \frac{\Lambda}{\beta}\right) R_2 e^{R_2 x_0} - 1.$$

**Remark 2.** Note that equations (24) and (25) reduce to equations (3.20) and (3.19) from [1] for  $\Lambda = 0$ . With (25), F(H) can be expressed as

$$F(H) = H^{\frac{-R_2}{R_1 - R_2}} \left( H + \frac{\Lambda}{\beta} \right)^{\frac{R_1}{R_1 - R_2}} \left( R_1 \left( \frac{R_2^2}{R_1^2} \right)^{\frac{R_1}{R_1 - R_2}} - R_2 \left( \frac{R_2^2}{R_1^2} \right)^{\frac{R_2}{R_1 - R_2}} \right) - 1.$$
(26)

We again need to show that  $x_0 > 0$ , which is certainly fulfilled if  $A_1 > 0$ , i.e. F(H) has to have a positive root which, due to the continuity of F(H) together with F(0) = -1 and  $\lim_{H\to\infty} F(H) = \infty$  is indeed the case. Moreover, the uniqueness of  $A_1$  follows from

$$F'(H) = \frac{H^{\frac{R_1}{R_2 - R_1}} \left(H + \frac{\Lambda}{\beta}\right)^{\frac{R_1}{R_1 - R_2}} \left(H\beta R_1 - R_2(H\beta + \Lambda)\right)}{(R_1 - R_2)(H\beta + \Lambda)} \left(R_1 \left(\frac{R_2^2}{R_1^2}\right)^{\frac{R_1}{R_1 - R_2}} - R_2 \left(\frac{R_2^2}{R_1^2}\right)^{\frac{R_2}{R_1 - R_2}}\right) > 0.$$

Lemma 4. The function

$$V^*(x) = \begin{cases} \frac{\Lambda}{\beta} + A_1 \ e^{R_1 x} - (A_1 + \frac{\Lambda}{\beta}) \ e^{R_2 x} & x < x_0, \\ x - x_0 + \frac{\Lambda}{\beta} + A_1 \ e^{R_1 x_0} - (A_1 + \frac{\Lambda}{\beta}) \ e^{R_2 x_0} & x \ge x_0, \end{cases}$$

is a twice differentiable and (strictly for  $x < x_0$ ) concave solution to the HJB equation (18).

*Proof.* It only remains to show that

$$V_l(x) = \frac{\Lambda}{\beta} + A_1 \ e^{R_1 x} - (A_1 + \frac{\Lambda}{\beta}) \ e^{R_2 x}$$

is strictly concave. Clearly  $V'_l(x) = A_1 R_1 e^{R_1 x} - (A_1 + \frac{\Lambda}{\beta}) R_2 e^{R_2 x} > 0$ . To see that  $V''_l(x) < 0$  for  $x < x_0$ , observe that

$$V_l''(0) = A_1 R_1^2 - R_2^2 \left(A_1 + \frac{\Lambda}{\beta}\right) < 0,$$
  

$$V_l''(x_0) = 0,$$
  

$$V_l'''(x) = A_1 R_1^3 e^{R_1 x} - \left(A_1 + \frac{\Lambda}{\beta}\right) R_2^3 e^{R_2 x} > 0.$$

Finally,  $V^{*'}(x) > 1$  for  $x < x_0$ .

**Proposition 5.** For every admissible dividend strategy L, the function  $V^*(x)$  of Lemma 4 dominates  $V(x, L), V^*(x) \ge V(x, L)$ . Let  $L^*$  be the barrier strategy given by the barrier  $x_0$ . Then  $V^*(x) = V(x, L^*)$ .

*Proof.* Let  $L = (L_t)_{t \ge 0}$  be any admissible strategy. From Dynkin's formula, see [18], we know that

$$e^{-\beta t \wedge \tau} V^*(R_{t \wedge \tau}^L) - V(x) - \int_0^{t \wedge \tau} e^{-\beta s} \mathbf{A} V^*(R_s^L) ds$$

is a martingale with expectation zero, where  $\mathbf{A}V^*(R_s^L)$  denotes the infinitesimal generator of the process  $R_t^L = x + \mu t + \int_0^t \sigma \, dW_s - L_t$ . To get the generator of the jump part of the process (which in this case can only originate from dividend payments) we use a generalized Itô formula from [6],

$$\begin{split} V^*(R_t^L) - V^*(R_0^L) &= \int_0^t V^{*'}(R_s^L) \, dR_s^{L,c} + \int_0^t \frac{\sigma^2}{2} V^{*''}(R_s^L) \, ds \\ &+ \sum_{\Delta R_s^L \neq 0, \ 0 \le s \le t} (V^*(R_{s-}^L + \Delta R_s^L) - V^*(R_{s-}^L)) \\ &= \int_0^t \mu V^{*'}(R_s^L) \, ds + \int_0^t \sigma V^{*'}(R_s^L) \, dW_s - \int_0^t V^*(R_s^L) dL_s^c \\ &+ \int_0^t \frac{\sigma^2}{2} V^{*''}(R_s^L) \, ds + \sum_{\Delta R_s^L \neq 0, \ 0 \le s \le t} (V^*(R_{s-}^L + \Delta R_s^L) - V^*(R_{s-}^L)), \end{split}$$

where the superscript c refers to the continuous component of the process. Note that the sum is negative because  $R_{s-}^L + \Delta R_s^L \leq R_{s-}^L$ . Concretely, we have

$$\mathbb{E}\left(e^{-\beta(t\wedge\tau)}V^{*}(R_{t\wedge\tau}^{L})\right) = V^{*}(x) + \mathbb{E}\left(\int_{0}^{t\wedge\tau} e^{-\beta s}\left(\mu V^{*'}(R_{s}^{L}) + \frac{\sigma^{2}}{2}V^{*''}(R_{s}^{L}) - \beta V^{*}(R_{s}^{L})\right) ds - \int_{0}^{t\wedge\tau} e^{-\beta s}V^{*'}(R_{s}^{L}) dL_{s}^{c} + \sum_{\Delta R_{s}^{L}\neq0,0\leq s\leq t\wedge\tau} e^{-\beta s}\left(V^{*}(R_{s-}^{L} + \Delta R_{s}^{L}) - V^{*}(R_{s-}^{L})\right)\right).$$

From the HJB equation (18) we get that the first integrand on the right side is smaller than  $-e^{-\beta s} \Lambda$ . Furthermore  $V^{*'} \geq 1$ . In addition, we have to find a bound for the left hand side and the sum. Because  $V^*(x)$  is concave, it can be bounded by a straight line of the form kx + d and so the left hand side is bounded by  $e^{-\beta t}(d + k|\mu t + \sigma W_t|)$  (note that for  $\tau < t$  we can use  $V^*(0) = 0$ ) and this term converges to zero for  $t \to \infty$ .

Jumps of the reserve occur if and only if jumps of the dividends occur, so  $R_s^L - R_{s-}^L = L_{s-} - L_s$ . Together with the concavity we get  $V^*(R_{s-}^L + \Delta R_s^L) - V^*(R_{s-}^L) \leq L_{s-} - L_s$ . Now we are allowed to let  $t \to \infty$  and together with the bounds above we get

$$\mathbb{E}\left(\int_0^\tau e^{-\beta s}\Lambda \,ds + \int_0^\tau e^{-\beta s} \,dL_s^c + \sum_{\Delta L_s \neq 0, 0 \le s \le \tau} e^{-\beta s} (L_s - L_{s-})\right)$$
$$= \mathbb{E}\left(\int_0^\tau e^{-\beta s}\Lambda \,ds + \int_0^\tau e^{-\beta s} \,dL_s\right) \le V^*(x)$$

Therefore  $V^*(x) \ge V(x, L)$  holds.

Now look at the barrier strategy  $L^*$  derived from  $x_0$ . We have that  $R_t^{L^*} \leq x_0$  for all  $t \geq 0$  and dividends are only paid at times at which  $R_t^{L^*} = x_0$ , note that  $V^{*'}(x)I_{x=x_0} = I_{x=x_0}$ . Because  $V^*$  fulfills the HJB equation (18) for  $x \leq x_0$  we get from Dynkin's formula,

$$\mathbb{E}\left(e^{-\beta t \wedge \tau} V^*(R_{t \wedge \tau}^{L^*})\right) = V^*(x) - \mathbb{E}\left(\int_0^{t \wedge \tau} e^{-\beta s} \Lambda \, ds - \int_0^{t \wedge \tau} e^{-\beta s} I_{R_s^{L^*} = x_0} \, dL_s^{*c} + \sum_{\Delta R_s^{L^*} \neq 0, 0 \le s \le t \wedge \tau} e^{-\beta s} \left(V^*(R_{s-}^{L^*} + \Delta R_s^{L^*}) - V^*(R_{s-}^{L^*})\right) \right)$$

From the construction of  $V^*$  and  $L^*$  jumps can only happen when  $R_s^{L^*} > x_0$  and

$$V^*(R_{s-}^{L^*} + \Delta R_s^{L^*}) - V^*(R_{s-}^{L^*}) = V^*(x_0) - (R_s^{L^*} - x_0 + V^*(x_0)) = -R_s^{L^*} + x_0 = L_{s-}^* - L_s^*$$

Therefore

$$\mathbb{E}\left(\int_{0}^{t\wedge\tau} e^{-\beta s} I_{R_{s}^{L^{*}}=x_{0}} \, dL_{s}^{*c} - \sum_{\Delta R_{s}^{L^{*}}\neq0,0\leq s\leq t\wedge\tau} e^{-\beta s} \left(V^{*}(R_{s-}^{L^{*}}+\Delta R_{s}^{L^{*}}) - V^{*}(R_{s-}^{L^{*}})\right)\right) = \mathbb{E}\left(\int_{0}^{t\wedge\tau} e^{-\beta s} \, dL_{s}^{*}\right)$$

As before all relevant terms are bounded and for  $t \to \infty$  we get the result

$$V^*(x) = \mathbb{E}\left(\int_0^\tau e^{-\beta t}\Lambda \,dt + \int_0^\tau e^{-\beta t} \,dL_t^*\right).$$

Figure 3 depicts the optimal dividend payout with unbounded intensity as a function of initial capital x for various values of  $\Lambda$  and Figure 4 shows the corresponding optimal barrier levels as a function of  $\Lambda$ .







Figure 4: Barrier as function of  $\Lambda$ 

### 3.3 Optimal Dividends and Proportional Reinsurance

In the literature for the diffusion model, optimal control problems were also extended to maximize expected dividend payments with additionally being able to take dynamic proportional reinsurance (see e.g. Hojgaard & Taksar [15]), where the insurer passes on some fraction  $0 \le 1 - A_t \le 1$  of the premiums (in the diffusion model of the drift  $\mu$ ), and correspondingly proportionally reduces the risk (in the diffusion model the volaitility  $\sigma$ ). This leads to the modified risk process

$$dR_t^A = A_t \ \mu dt + A_t \ \sigma dW_t$$

for the dynamic reinsurance strategy  $A = (A_t)_{t \ge 0}$ . A strategy is admissible if it is an adapted process and  $0 \le A_t \le 1$  for all  $t \ge 0$ . It is natural to ask for the optimal combination of dividend and reinsurance strategy maximizing

$$V(x, A, L) = \mathbb{E}\left(\int_0^\tau e^{-\beta t} dL_t + \int_0^\tau e^{-\beta t} \Lambda dt \mid R_0^{A, L} = x\right)$$

among all admissible strategies A and L. However, since for  $\Lambda = 0$  the optimal reinsurance strategy is to pass on all the risk  $(A^*(0) = 0)$  and stay at zero forever, this means that ruin can not occur for this controlled process and hence we always obtain the maximal reward  $\frac{\Lambda}{\beta}$  from the second summand of our value function. Consequently, the optimal strategy is not influenced by this additional term and  $V^*(x)$  is always given by the value for  $\Lambda = 0$  (already determined in [15]) plus  $\frac{\Lambda}{\beta}$ . If one formulates and solves the HJB equation for  $\Lambda > 0$ , the above conclusion is reflected by the fact that the initial condition  $V^*(0) = \frac{\Lambda}{\beta}$ neutralizes the additional factor  $\Lambda$  in the differential equations arising from the HJB equation.

# 4 Optimal strategy for the Cramér-Lundberg model

In this section we will investigate the impact of the term  $\Lambda$  for the optimal dividend payout scheme for the Cramér-Lundberg model (1), where in addition we assume exponentially distributed claim amounts. In the Cramér-Lundberg model the value function does not satisfy the boundary condition V(0) = 0(since being in 0 does now not necessarily imply ruin) and hence we have to look for another condition.

### 4.1 Bounded dividend intensity

Let us start again with the case of a bounded dividend intensity  $0 \le l_t \le M$  for a bound  $0 \le M < c$ . The generator of the controlled risk reserve process is given by

$$\mathbf{A}g(x) = (c-l)g'(x) + \lambda \int_0^x g(x-y) - g(x) \, dF_Y(y).$$
(27)

Now g(x) is not continuous in 0. Such a case can be handled by introducing the concept of a stopped risk reserve process (by considering an additional dimension with two states, reflecting "stopped" or "unstopped"). For details of this technique in the framework of *Piecewise Deterministic Markov Processes* see Rolski et al. [18]. The HJB equation in the bounded case reads as follows

$$0 = \sup_{0 \le l \le M} \left\{ \Lambda + l + (c - l)V'(x) + \lambda \int_0^x V(x - y)dF_Y(y) - (\beta + \lambda)V(x) \right\}.$$
 (28)

From now on we specify  $F_Y(y) = 1 - e^{-\alpha y}$  and assume the existence of a strictly increasing concave solution of (28). Because of the linearity in the control l we get a crucial point  $x_0$  with V'(x) > 1 for  $x < x_0$ ,  $V'(x_0) = 1$  and V'(x) < 1 for  $x > x_0$ . As in Section 3, it is possible that  $x_0 = 0$ . Under these assumptions the HJB equation (28) is equal to

$$0 = \Lambda + cV'(x) + \lambda \int_0^x V(x-y)\alpha e^{-\alpha y} dy - (\beta + \lambda)V(x), \quad x \le x_0,$$
(29)

$$0 = \Lambda + M + (c - M)V'(x) + \lambda \int_0^x V(x - y)\alpha e^{-\alpha y} dy - (\beta + \lambda)V(x), \quad x > x_0.$$
(30)

Equation (29) can be rewritten as

$$cV''(x) + (\alpha c - (\beta + \alpha))V'(x) - \alpha\beta V(x) + \alpha\Lambda = 0$$

with a general solution of the form

$$V_l(x) = \frac{\Lambda}{\beta} + A_1 e^{R_1 x} + A_2 e^{R_2 x}$$

where

$$R_{1,2} = -\frac{(\alpha c - (\beta + \lambda))}{2c} \pm \sqrt{\frac{(\alpha c - (\beta + \lambda))^2}{4c^2} + \frac{\alpha \beta}{c}}.$$

Clearly  $R_2 < 0 < R_1$  and  $|R_1| < |R_2|$ . Correspondingly, (30) has a solution of the form

$$V_r(x) = \frac{\Lambda + M}{\beta} + B_1 e^{S_1 x} + B_2 e^{S_2 x}$$

with

$$S_{1,2} = -\frac{(\alpha(c-M) - (\beta + \lambda))}{2(c-M)} \pm \sqrt{\frac{(\alpha(c-M) - (\beta + \lambda))^2}{4(c-M)^2} + \frac{\alpha\beta}{(c-M)}}$$

and  $S_2 < 0 < S_1$ ,  $R_2 < S_2$ . The value function is bounded by  $\frac{\Lambda+M}{\beta}$ , so that  $B_1 = 0$  and  $B_2 < 0$ . If  $x_0 = 0$  (i.e. it is optimal to pay dividends at rate M for any initial capital  $x \ge 0$ ), then the value function has to fulfill (30) for all  $x \ge 0$ . Putting  $V_r(x)$  into (30) gives

$$V_r(x) = \frac{\Lambda + M}{\beta} \left( 1 - \frac{\alpha + S_2}{\alpha} e^{S_2 x} \right).$$

This function is increasing and concave, because  $\alpha + S_2 > 0$ . It is indeed the optimal solution if  $V'_r(0) \le 1$ , which happens if  $-\frac{(\alpha+S_2)}{\alpha\beta}S_2(\Lambda+M) \le 1$ .

From now on we consider the opposite case  $-\frac{(\alpha+S_2)}{\alpha\beta}S_2(\Lambda+M) > 1$ . Since we need a differentiable solution of (29) and (30), the following three equations have to hold in  $x_0$ :

$$\frac{\Lambda}{\beta} + A_1 e^{R_1 x_0} + A_2 e^{R_2 x_0} = \frac{\Lambda + M}{\beta} + B_2 e^{S_2 x_0}, \qquad (31)$$

$$A_1 R_1 e^{R_1 x_0} + A_2 R_2 e^{R_2 x_0} = B_2 S_2 e^{S_2 x_0} = 1.$$
(32)

With the notation  $\delta(M) := \frac{M}{\beta} + \frac{1}{S_2}$ , we obtain from (31)

$$x_0 = \frac{1}{R_1 - R_2} \log \left( -\frac{A_2(x_0)}{A_1(x_0)} \frac{1 - \delta(M) R_2}{1 - \delta(M) R_1} \right).$$
(33)

Again we have highlighted the dependence of the coefficients  $A_i$  on  $x_0$  to see that the equation is not explicit in  $x_0$  (opposed to the case  $\Lambda = 0$ ). Given  $x_0$ , (31) together with substitution of  $V_l$  and  $V_r$  in (29) and (30) imply that the coefficients are the solution of the linear system of equations

$$\begin{pmatrix} e^{R_1x_0} & e^{R_2x_0} & -e^{S_2x_0} \\ \frac{\alpha}{\alpha+R_1} & \frac{\alpha}{\alpha+R_2} & 0 \\ \frac{\alpha}{\alpha+R_1} & \frac{\alpha}{\alpha+R_2} & -\frac{\alpha}{\alpha+S_2} \end{pmatrix} \begin{pmatrix} A_1 \\ A_2 \\ B_2 \end{pmatrix} = \begin{pmatrix} \frac{M}{\beta} \\ -\frac{\Lambda}{\beta} \\ \frac{M}{\beta} \end{pmatrix}.$$

From the right equality (32) we directly get  $B_2 = \frac{e^{-S_2 x_0}}{S_2} < 0$  (which coincides with the solution from the system only if  $V'(x_0)$  exists and equals 1). Then

$$A_{1} = \frac{(\alpha + R_{1})(e^{R_{2}x_{0}}\Lambda(R_{2} - S_{2}) - MS_{2})}{\alpha\beta(e^{R_{1}x_{0}}(R_{1} - S_{2}) + e^{R_{2}x_{0}}(S_{2} - R_{2}))},$$
  

$$A_{2} = \frac{(\alpha + R_{2})(e^{R_{1}x_{0}}\Lambda(R_{1} - S_{2}) - MS_{2})}{\alpha\beta(e^{R_{2}x_{0}}(R_{2} - S_{2}) + e^{R_{1}x_{0}}(S_{2} - R_{1}))}.$$
(34)

Here  $A_2 < 0$  for any value of  $x_0$ , whereas  $A_1 > 0$  if  $x_0 > \frac{1}{R_2} \log \left( \frac{MS_2}{\Lambda(R_2 - S_2)} \right)$ .

**Lemma 6.** For M < c we have

$$\frac{1}{R_2} < \delta(M) < \frac{1}{R_1}.$$

*Proof.* Define  $H(M) := \delta(M) - \frac{1}{R_1(M)}$ . Then  $H(0) = \frac{1}{R_2} - \frac{1}{R_1} < 0$ . From

$$\lim_{M \to c^-} S_2 = \lim_{M \to c^-} -\frac{\alpha}{2} + \frac{(\beta + \lambda)}{2(c - M)} - \frac{1}{(c - M)} \sqrt{\frac{\alpha^2 (c - M)^2 + (\beta + \lambda)^2 - 2\alpha(\beta + \lambda)(c - M)}{4}} + \alpha\beta(c - M)$$
$$= \lim_{M \to c^-} -\frac{\alpha}{2} + \frac{-\frac{\alpha^2 (c - M)}{4} + \frac{\alpha(\beta + \lambda)}{2} - \alpha\beta}{\frac{(\beta + \lambda)}{2} + \sqrt{\frac{\alpha^2 (c - M)^2 + (\beta + \lambda)^2 - 2\alpha(\beta + \lambda)(c - M)}{4}} + \alpha\beta(c - M)}$$
$$= -\frac{\alpha\beta}{(\beta + \lambda)} < 0$$

we get

$$\lim_{M \to c^{-}} H(M) = \frac{\alpha c - (\beta + \lambda)}{\alpha \beta} - \frac{\frac{(\alpha c - (\beta + \lambda))}{2} + \sqrt{\frac{(\alpha c - (\beta + \lambda))^2}{4} + \alpha \beta c}}{\alpha \beta} < 0.$$

The monotonicity of H(M) in  $\in [0, c)$  follows from

$$H'(M) = \frac{2\lambda}{\alpha^2(c-M)^2 + (\beta+\lambda)^2 + 2\alpha(\beta-\lambda)(c-M) - (\alpha c + \beta - \lambda)\sqrt{\alpha^2(c-M)^2 + (\beta+\lambda)^2 + 2\alpha(\beta-\lambda)(c-M)}}$$

Indeed, for  $(\alpha c + \beta - \lambda) < 0$  we immediately have H'(M) > 0. In the opposite case  $(\alpha c + \beta - \lambda) > 0$  one observes

$$(\alpha c + \beta - \lambda) < \sqrt{\alpha^2 (c - M)^2 + (\beta + \lambda)^2 + 2\alpha(\beta - \lambda)(c - M)} \Leftrightarrow \alpha^2 (c - M)^2 + (\beta - \lambda)^2 + 2\alpha(\beta - \lambda)(c - M) < \alpha^2 (c - M)^2 + (\beta + \lambda)^2 + 2\alpha(\beta - \lambda)(c - M) \Leftrightarrow 0 < 4\beta\lambda,$$

also implying H'(M) > 0. Hence H(M) < 0 for  $M \in [0, c)$ . For the second inequality, define  $H_1(M) := \delta - \frac{1}{R_2} > 0$ .  $H'_1(M) = \frac{\partial}{\partial M} \left(\frac{M}{\beta} + \frac{1}{S_2}\right) = H'(M) > 0$  and hence  $H_1(M)$  is strictly increasing for  $M \in [0, c)$ . Furthermore, for  $M = \frac{\beta c}{\alpha c - \lambda}$  we have  $\delta = 0$ . Therefore  $H_1(0) = 0$  and  $H_1\left(\frac{\beta c}{\alpha c - \lambda}\right) = -\frac{1}{R_2} > 0$  and finally  $H_1(M) > 0$  for  $M \in (0, \frac{\beta c}{\alpha c - \lambda})$ . For  $M \ge \frac{\beta c}{\alpha c - \lambda}$ , the term  $\delta$  is positive and so  $(1 - \delta R_2) > 0$  also holds for this case.

From (33) and (34) one sees that  $x_0$  is the solution of the nonlinear equation

$$x = \frac{1}{R_1 - R_2} \log \left( \frac{\alpha + R_2}{\alpha + R_1} \frac{(e^{R_1 x} \Lambda (R_1 - S_2) - MS_2)}{(e^{R_2 x} \Lambda (R_2 - S_2) - MS_2)} \frac{(\beta (R_2 - S_2) + MR_2 S_2)}{(\beta (R_1 - S_2) + MR_1 S_2)} \right).$$
(35)

**Remark 3.** Note that for  $\Lambda = 0$  equation (35) reduces to equation (9.15) of Gerber & Shiu [11]. **Lemma 7.** For  $-\frac{(\alpha+S_2)}{\alpha\beta}S_2(\Lambda+M) > 1$  equation (35) has an unique positive solution  $x_0$ . *Proof.* To simplify notation, define

$$G(x) := \frac{1}{R_1 - R_2} \log \left( \frac{\alpha + R_2}{\alpha + R_1} \frac{(e^{R_1 x} \Lambda (R_1 - S_2) - MS_2)}{(e^{R_2 x} \Lambda (R_2 - S_2) - MS_2)} \frac{(\beta (R_2 - S_2) + MR_2S_2)}{(\beta (R_1 - S_2) + MR_1S_2)} \right).$$

Note that

$$\frac{\beta(R_2 - S_2) + MR_2S_2}{\beta(R_1 - S_2) + MR_1S_2} = \frac{1 - \delta R_2}{1 - \delta R_1}$$

and observe

$$\lim_{x \to \infty} G'(x) = \frac{R_1}{R_1 - R_2} < 1.$$

This means that for large x, G(x) tends to a linear function with slope less than one. Furthermore

$$\begin{split} G''(x) &= \frac{e^{(R_1+2R_2)x} \left(-\Lambda^3 M R_1^2 S_2(R_1-S_2)(R_2-S_2)^2\right) + e^{(2R_1+R_2)x} \left(\Lambda^3 M R_2^2 S_2(R_1-S_2)^2(R_2-S_2)\right)}{(R_1-R_2) \left(e^{R_1x} \Lambda(R_1-S_2) - M S_2\right)^2 \left(e^{R_2x} \Lambda(R_2-S_2) - M S_2\right)^2} \\ &+ \frac{e^{(R_1+R_2)x} (2\Lambda^2 M^2 S_2^2(R_1-R_2)(R_1+R_2)(R_1-S_2)(R_2-S_2)) + e^{R_1x} (\Lambda M^3 R_1^2 S_2^3(S_2-R_1))}{(R_1-R_2) \left(e^{R_1x} \Lambda(R_1-S_2) - M S_2\right)^2 \left(e^{R_2x} \Lambda(R_2-S_2) - M S_2\right)^2} \\ &+ \frac{e^{R_2x} (\Lambda M^3 R_2^2 S_2^3(R_2-S_2)}{(R_1-R_2) \left(e^{R_1x} \Lambda(R_1-S_2) - M S_2\right)^2 \left(e^{R_2x} \Lambda(R_2-S_2) - M S_2\right)^2} > 0, \end{split}$$

since all coefficients of the exponential terms are positive. Hence G(x) is convex. It has a pole at  $\hat{x} = \frac{1}{R_2} \log \left( \frac{MS_2}{\Lambda(R_2 - S_2)} \right)$  with

$$\lim_{x \to \hat{x}^+} G(x) = \infty.$$

If  $\hat{x} \ge 0$  (which holds for  $S_2 \ge \frac{R_2 \Lambda}{(\Lambda + M)}$ ) this implies the existence of a unique positive root  $x_0$  of x = G(x). If  $\hat{x} < 0$  (i.e.  $S_2 < \frac{\Lambda R_2}{(\Lambda + M)}$ ), one can consider

$$G(0) = \frac{1}{(R_1 - R_2)} \log \left( \frac{(\alpha + R_2)}{(\alpha + R_1)} \frac{(1 - \delta R_2)}{(1 - \delta R_1)} \frac{\Lambda R_1 - (\Lambda + M)S_2}{\Lambda R_2 - (\Lambda + M)S_2} \right).$$

Here all terms of the denominator are positive and G(0) > 0 is equivalent to

$$(\alpha + R_2)(1 - \delta R_2)(\Lambda R_1 - (\Lambda + M)S_2) - (\alpha + R_1)(1 - \delta R_1)(\Lambda R_2 - (\Lambda + M)S_2) > 0.$$

From  $\alpha + R_1 > \alpha + R_2 > 0$  we have that the expression above is greater than

$$M(R_1 - R_2)(\alpha + R_2)S_2(\beta + (\Lambda + M)S_2),$$

which is positive because

$$\beta < \frac{\alpha\beta}{(\alpha + S_2)} < -S_2(\Lambda + M).$$

Hence G(0) > 0 and again the existence of a unique root  $x_0$  of x = G(x) follows.

Lemma 8. If  $-\frac{(\alpha+S_2)}{\alpha\beta}S_2(\Lambda+M) \leq 1$  then

$$V^*(x) = \frac{\Lambda + M}{\beta} \left( 1 - \frac{(\alpha + S_2)}{\alpha} e^{S_2 x} \right)$$

is a differentiable, increasing and concave solution of the HJB equation (28). If  $-\frac{(\alpha+S_2)}{\alpha\beta}S_2(\Lambda+M) > 1$ , then

$$V^*(x) = \begin{cases} \frac{\Lambda}{\beta} + A_1 \ e^{R_1 x} + A_2 \ e^{R_2 x} & x \le x_0, \\ \frac{\Lambda + M}{\beta} + B_2 \ e^{S_2 x} & x_0 < x \end{cases}$$

with  $x_0$  the unique solution of (35) and  $A_1, A_2, B_2$  determined by the equations given above, is a differentiable increasing and concave solution to (28).

*Proof.* It only remains to show that for  $-\frac{(\alpha+S_2)}{\alpha\beta}S_2(\Lambda+M) > 1$  one indeed has  $V^{*'}(x) > 1$  for  $x < x_0$ ,  $\alpha_{\beta} = 2(1 + 4x) \times 1$  one indeed has  $V(x) \times 1$  for  $x < x_0$ ,  $0 < V^{*'}(x) < 1$  for  $x_0 < x$  and  $V^{*''}(x) < 0$  for  $x \ge 0$ . Due to  $A_1 > 0$ ,  $A_2 < 0$  and  $B_2 < 0$ , together with  $V^{*'}(x_0) = 1$  this holds for  $x > x_0$ . For  $x < x_0$ ,  $V^{*''}(x) < 0$  follows if

$$x_0 \le \frac{1}{R_1 - R_2} \log \left( \frac{R_2^2}{R_1^2} \frac{(\alpha + R_2)}{(\alpha + R_1)} \frac{(e^{R_1 x_0} \Lambda(R_1 - S_2) - MS_2)}{(e^{R_2 x_0} \Lambda(R_2 - S_2) - MS_2)} \right) \Longleftrightarrow R_2^2 (1 - \delta R_1) > R_1^2 (1 - \delta R_2).$$



Figure 5: Value function for  $\Lambda = 0, 0.5, 1, 1.5, 2$ 

However, the last inequality holds because

$$R_2^2(1-\delta R_2) - R_1^2(1-\delta R_2) = -\frac{\sqrt{\beta^2 + (\alpha c - \lambda)^2 + 2\beta(\alpha c + \lambda)} \left(\beta + \lambda - \alpha(c - M) - \sqrt{(\alpha(c - M) - (\beta + \lambda))^2 + 4\alpha\beta(c - M)}\right)}{2c^2},$$

and

$$\left(\beta + \lambda - \alpha(c - M) - \sqrt{(\alpha(c - M) - (\beta + \lambda))^2 + 4\alpha\beta(c - M)}\right) < 0.$$

**Proposition 9.** The function  $V^*(x)$  given in Lemma 8 fulfills  $V^*(x) = V(x)$  and the threshold strategy with threshold level  $x_0$  is optimal among all admissible strategies with bounded density in the case of  $Exp(\alpha)$  distributed claim amounts.

*Proof.* Use the generator of the controlled process given in (27) and proceed in exactly the same way as in Proposition 3.  $\Box$ 

Figure 5 depicts the value function for initial capital x for several values of  $\Lambda$  and Figure 6 shows the threshold level as a function of  $\Lambda$  for the parameter set  $\alpha = 2$ ,  $\lambda = 3$ ,  $\beta = 0.03$ , c = 1.75 and M = 1. One can again observe that  $x_0$  is increasing in  $\Lambda$ .

### 4.2 Unbounded dividend intensity

If the dividend intensity is not bounded, the associated HJB equation reads as follows

$$\max\left\{\Lambda + cV'(x) + \lambda \int_0^x V(x-y)dF_Y(y) - (\beta + \lambda)V(x), 1 - V'(x)\right\} = 0.$$
 (36)

We again consider the special case of  $Exp(\alpha)$  distributed claim amounts and first assume the existence of a concave differentiable solution to (36). The crucial point where the first derivative of the value function becomes smaller than one is again denoted by  $x_0$ . For  $x > x_0$  we then have 1 - V'(x) = 0, which immediately gives  $V(x) = x + B_2$  for some constant  $B_2$ . For  $x \le x_0$ , we have to solve

$$\Lambda + cV'(x) + \lambda \int_0^x V(x-y)\alpha \ e^{-\alpha y} dy - (\beta + \lambda)V(x) = 0, \tag{37}$$

which can be rewritten as

$$cV''(x) + (\alpha c - (\beta + \lambda))V'(x) - \alpha\beta V(x) + \alpha\Lambda = 0,$$



Figure 6: Barrier as function of  $\Lambda$ 

with general solution

$$V_l(x) = \frac{\Lambda}{\beta} + A_1 e^{R_1 x} + A_2 e^{R_2 x}$$

where the exponents  $\{R_1, R_2\}$  are again the roots of the polynomial

$$P(R) = cR^2 + (\alpha c - (\beta + \lambda))R - \alpha\beta.$$

Substitution in (37) then leads to

$$A_2 = -\frac{\alpha + R_2}{\alpha} \left( \frac{\alpha}{\alpha + R_1} A_1 + \frac{\Lambda}{\beta} \right).$$

We now need to find a differentiable solution. The corresponding pasting conditions at  $x_0$  give  $B_2 = -x_0 + V_l(x_0)$  and  $V'_l(x_0) = 1$ , yielding

$$A_1 = \frac{(\alpha + R_1)(\alpha\beta + e^{R_2 x_0} \Lambda R_2(\alpha + R_2))}{\alpha\beta(e^{R_1 x_0} R_1(\alpha + R_1) - e^{R_2 x_0} R_2(\alpha + R_2))}.$$

We are still short of an additional condition to determine  $x_0$ . In the diffusion case of Section 3.2, this additional condition was the request of a twice differentiable solution, implying  $V''(x_0) = 0$ . Here we do not have second derivatives in the equations. Nevertheless,  $V''(x_0) = 0$  also turns out to be the appropriate condition in this case: Above we have seen that the coefficients  $\{A_1, A_2\}$  are functions of the barrier  $x_0$ . Denote this barrier by *b* for a moment. Some calculations show that the optimal barrier height is then determined by setting

$$\frac{\partial}{\partial b} \left( \frac{\Lambda}{\beta} + A_1(b) \ e^{R_1 x} + A_2(b) \ e^{R_2 x} \right) = -\frac{(\alpha + R_1) \ e^{R_1 x} - (\alpha + R_2) \ e^{R_2 x}}{R_1(\alpha + R_1) \ e^{R_1 b} - R_2(\alpha + R_2) \ e^{R_2 b}} \ V_b''(b) = 0, \tag{38}$$

where  $V_b(x)$  is the value function belonging to a specified barrier b, given by

$$V_b(x) = \begin{cases} \frac{\Lambda}{\beta} + A_1(b) \ e^{R_1 x} + A_2(b) \ e^{R_2 x} & x \le b, \\ x - b + V_b(b) & x > b. \end{cases}$$

The denominator of the right-hand side of (38) is strictly positive, therefore we have to find a root of  $V_b''(b)$  to obtain the optimal barrier. In the following we will show that  $V_b''(b)$  has an unique root giving the optimal value function and therefore the optimal barrier.  $V_b''(b) = 0$  is equivalent to

$$A_1 R_1^2 e^{R_1 x_0} + A_2 R_2^2 e^{R_2 x_0} = 0$$

which leads to

$$x_{0} = \frac{1}{R_{1} - R_{2}} \log \left( \frac{R_{2}^{2}}{R_{1}^{2}} \frac{(\alpha + R_{2})}{(\alpha + R_{1})} \frac{(\alpha \beta + e^{R_{1}x_{0}}(\alpha + R_{1})\Lambda R_{1})}{(\alpha \beta + e^{R_{2}x_{0}}(\alpha + R_{2})\Lambda R_{2})} \right).$$
(39)

**Remark 4.** For  $\Lambda = 0$ , equation (39) again reduces to equation (5.2.6) of Gerber [9]. Lemma 10. If  $\alpha\lambda(c + \Lambda) - (\beta + \lambda)^2 \leq 0$  then

$$V^*(x) = x + \frac{c + \Lambda}{\beta + \lambda},$$

is a solution of (36). If  $\alpha\lambda(c+\Lambda) - (\beta+\lambda)^2 > 0$ , then the function

$$V^*(x) = \begin{cases} \frac{\Lambda}{\beta} + A_1(x_0) \ e^{R_1 x} + A_2(x_0) \ e^{R_2 x} & x \le x_0, \\ x - x_0 + V^*(x_0) & x > x_0 \end{cases}$$

is a concave solution to (36), where  $x_0$  is the unique root of equation (39).

*Proof.* We start with looking at the case  $\alpha\lambda(c+\Lambda) - (\beta+\lambda)^2 \leq 0$ . It is obvious that  $V^*(x) = x + \frac{c+\Lambda}{\beta+\lambda}$  solves  $1 - V^{*'}(x) = 0$ . Thus we have to show that the first part of the left hand side of (36) is not positive. Substituting  $V^*(x) = x + \frac{c+\Lambda}{\beta+\lambda}$  into (36) we thus have to show that

$$(e^{-\alpha x}-1) \frac{\beta \lambda + \lambda^2 - \alpha \lambda (c+\Lambda)}{\alpha (\beta+\lambda)} - \beta x \le 0,$$

which clearly holds in zero. With  $\beta \lambda + \lambda^2 - \alpha \lambda (c + \Lambda) \leq -\beta (\beta + \lambda)$  we indeed have

$$(e^{-\alpha x}-1) \frac{\beta \lambda + \lambda^2 - \alpha \lambda (c+\Lambda)}{\alpha (\beta+\lambda)} \le \frac{\beta}{\alpha} (1-e^{-\alpha x}) \le \beta x.$$

Note that the second inequality is strict for x > 0. On the barrier (which is equal to zero), both terms of (36) are equal to zero, while for x > 0 the first one is strictly negative.

From now on we deal with the case  $\alpha\lambda(c+\Lambda) - (\beta+\lambda)^2 > 0$ . Here  $x + \frac{(c+\Lambda)}{(\beta+\lambda)}$  is not a solution to (36): The first part of the maximum in (36) gives

$$(1 - e^{-\alpha x}) \frac{\alpha \lambda (c + \Lambda) - (\beta + \lambda)\lambda}{\alpha (\beta + \lambda)} - \beta x, \qquad (40)$$

which is zero for x = 0, but for

$$0 \le x < \frac{1}{\alpha} \log \left( \frac{\alpha \lambda (c - \Lambda) - (\beta + \lambda) \lambda}{\beta (\beta + \lambda)} \right),$$

the first derivative of (40) is strictly positive and therefore the first part in the maximum of (36) is positive, so that the line  $x + \frac{(c+\Lambda)}{(\beta+\lambda)}$  does not solve (36).

Next we show that (39) has a unique positive solution denoted by  $x_0$ . Let

$$F(x) := \frac{1}{R_1 - R_2} \log \left( \frac{R_2^2}{R_1^2} \frac{(\alpha + R_2)}{(\alpha + R_1)} \frac{(\alpha \beta + e^{R_1 x} (\alpha + R_1) \Lambda R_1)}{(\alpha \beta + e^{R_2 x} (\alpha + R_2) \Lambda R_2)} \right).$$

We have

$$\lim_{x \to \infty} F'(x) = \frac{\Lambda^2 R_2(\alpha + R_2)(R_1 - R_2) + \alpha \beta R_1}{\alpha \beta (R_1 - R_2)} < 1.$$

Consequently, for large values of x the right hand side of (39) grows linearly with smaller slope than the left hand side, so that a desired solution exists if F(x) > x, for some x > 0. The numerator in the logarithm above is positive. Furthermore, the denominator is positive for  $x > \hat{x}$ 

where  $\frac{1}{2}$ 

$$\hat{x} = \frac{1}{R_2} \log \left( \frac{-\alpha\beta}{\lambda R_2(\alpha + R_2)} \right)$$
$$\lim_{x \to \hat{x}^+} F(x) = \infty.$$

and

As result we get that if  $\hat{x} \ge 0$ , then a positive root  $x_0$  of (39) exists. For  $\hat{x} < 0$  (i.e.  $\Lambda R_2(\alpha + R_2) + \alpha\beta > 0$ ), consider

$$F(0) = \frac{1}{R_1 - R_2} \log \left( \frac{(\alpha\beta + \Lambda R_1(\alpha + R_1))R_2^2(\alpha + R_2)}{(\alpha\beta + \Lambda R_2(\alpha + R_2))R_1^2(\alpha + R_1)} \right)$$

and F(0) > 0 if

$$(\alpha\beta + \Lambda R_1(\alpha + R_1))R_2^2(\alpha + R_2) - (\alpha\beta + \Lambda R_2(\alpha + R_2))R_1^2(\alpha + R_1) = \frac{\alpha\beta\sqrt{\frac{\beta^2 + 2\beta(\alpha c + \lambda) + (\lambda - \alpha c)^2}{c^2}}(\alpha\lambda(c + \Lambda) - (\beta + \lambda)^2)}{c^2} > 0,$$

which holds under the condition  $\alpha\lambda(c+\Lambda) - (\beta+\lambda)^2 > 0$  of the lemma. Finally, the uniqueness of  $x_0$  follows by verifying that F''(x) > 0 and hence convexity of F(x), which can be done by some algebraic manipulations.

For  $x \ge x_0$ , the concavity of V(x) is obvious. For  $x < x_0$  the first and second derivatives are

$$V'(x) = \frac{e^{R_1 x} R_1(\alpha + R_1)(\alpha \beta + e^{R_2 x_0} \Lambda R_2(\alpha + R_2) - e^{R_2 x} R_2(\alpha + R_2)(\alpha \beta + e^{R_1 x_0} \Lambda R_1(\alpha + R_1))}{\alpha \beta (e^{R_1 x_0} R_1(\alpha + R_1) - e^{R_2 x_0} R_2(\alpha + R_2))},$$
  

$$V''(x) = \frac{e^{R_1 x} R_1^2(\alpha + R_1)(\alpha \beta + e^{R_2 x_0} \Lambda R_2(\alpha + R_2) - e^{R_2 x} R_2^2(\alpha + R_2)(\alpha \beta + e^{R_1 x_0} \Lambda R_1(\alpha + R_1))}{\alpha \beta (e^{R_1 x_0} R_1(\alpha + R_1) - e^{R_2 x_0} R_2(\alpha + R_2))},$$

and V'(x) > 0 follows. Also, the definition of  $x_0$  implies V''(x) < 0 for  $x < x_0$  and, as mentioned before, we get that V''(x) > 0 for  $x > x_0$ . Therefore  $x_0$  is the only root of V''(x).

**Proposition 11.** For  $Exp(\alpha)$  distributed claim amounts a barrier strategy characterized by  $x_0$  is optimal among all admissible strategies and the function  $V^*(x)$  defined in Lemma 10 is the value function V(x).

*Proof.* Because under the assumptions of the proposition a unique solution of the HJB equation (36) exists, the result can be proved in exactly the same way as in Proposition 5.  $\Box$ 

Figure 7 shows V(x) as a function of initial capital x for several values of  $\Lambda$ , whereas Figure 8 depicts the optimal barrier level as a function of  $\Lambda$  for the same set of parameters underlying Figures 5 and Figure 6. Finally, Figure 9 shows the corresponding expected discounted dividends for three values of  $\Lambda$  (where  $\Lambda = 0$  again refers to the case of pure dividend maximization). A formula for the expected ruin time under a horizontal barrier strategy and exponential claim amounts can for instance be found in Lin et al. [17] and an application of that formula for the respective values of  $x_0(\Lambda)$  gives the functions depicted in Figure 10. A comparison of Figures 9 and 10 reveals that for the used set of parameters the increase of the barrier  $x_0$  due to a positive value of  $\Lambda$  leads to a much larger expected ruin time whereas the dividend reduction is moderate.

# References

- S. Asmussen and M. Taksar. Controlled diffusion models for optimal dividend pay-out. Insurance Math. Econom., 20(1):1-15, 1997.
- [2] P. Azcue and N. Muler. Optimal reinsurance and dividend distribution policies in the Cramér-Lundberg model. Math. Finance, 15(2):261-308, 2005.
- [3] N. Bäuerle. Approximation of optimal reinsurance and dividend payout policies. Math. Finance, 14(1): 99–113, 2004.
- [4] E. Boguslavskaya. On optimization of dividend flow for a company in the presence of liquidation value. *Working paper*, 2003.
- [5] S. Browne. Optimal investment policies for a firm with a random risk process: exponential utility and minimizing the probability of ruin. *Math. Oper. Res.*, 20(4):937–958, 1995.
- [6] R. Cont and P. Tankov. Financial modelling with jump processes. Chapman & Hall/CRC Financial Mathematics Series. Boca Raton, 2004.



Figure 7: Value function for  $\Lambda=0,\ 0.5,\ 1,\ 1.5,\ 2$ 



Figure 9: Pure dividend payments for  $\Lambda = 0, 1, 2$ 



Figure 10: Expected time of ruin for  $\Lambda = 0, 1, 2$ 

- [7] W. H. Fleming and H. M. Soner. Controlled Markov processes and viscosity solutions, volume 25 of Applications of Mathematics. Springer, New York, 1993.
- [8] J. Gaier and P. Grandits. Ruin probabilities in the presence of regularly varying tails and optimal investment. Insurance Math. Econom., 30(2):211-217, 2002.
- [9] H. U. Gerber. Entscheidungskriterien fuer den zusammengesetzten Poisson-Prozess. Schweiz. Aktuarver. Mitt., (1):185–227, 1968.
- [10] H. U. Gerber, X.S. Lin and H. Yang. A note on the dividends-penalty identity and the optimal dividend barrier. *Preprint*, 2006.
- [11] H. U. Gerber and E. S. W. Shiu. On optimal dividend strategies in the compound Poisson model. North American Actuarial Journal, 10(2):76–93, 2006.
- [12] J. Grandell. A class of approximations of ruin probabilities. Scand. Actuar. J., (suppl.):37–52, 1977.
- [13] C. Hipp and M. Plum. Optimal investment for insurers. Insurance Math. Econom., 27(2):215–228, 2000.
- [14] C. Hipp and M. Vogt. Optimal dynamic XL reinsurance. Astin Bull., 33(2):193–207, 2003.
- [15] B. Højgaard and M. Taksar. Controlling risk exposure and dividends payout schemes: insurance company example. *Math. Finance*, 9(2):153–182, 1999.
- [16] D. L. Iglehart. Diffusion approximations in collective risk theory. J. Appl. Probability, 6:285-292, 1969.
- [17] X. S. Lin, G. E. Willmot and S. Drekic. The classical risk model with a constant dividend barrier: analysis of the Gerber-Shiu discounted penalty function. *Insurance Math. Econom.*, 33(3):551-566, 2003.
- [18] T. Rolski, H. Schmidli, V. Schmidt, and J. Teugels. Stochastic processes for insurance and finance. Wiley Series in Probability and Statistics. John Wiley & Sons Ltd., Chichester, 1999.
- [19] H. Schmidli. Optimal proportional reinsurance policies in a dynamic setting. Scand. Actuar. J., (1):55-68, 2001.
- [20] H. Schmidli. On minimizing the ruin probability by investment and reinsurance. Ann. Appl. Probab., 12(3):890-907, 2002.
- [21] H. Schmidli. Diffusion Approximations. In: Teugels, J.L. and Sundt, B. (ed.) Encyclopedia of Actuarial Sciences, Vol. 1. J. Wiley and Sons, Chichester, 2004.

- [22] H. Schmidli. Optimal control in insurance. Springer, Berlin, 2006.
- [23] M. I. Taksar. Optimal risk and dividend distribution control models for an insurance company. Math. Methods Oper. Res., 51(1):1-42, 2000.