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PRESENT VALUE OF A RENEWAL PROCESS

by

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0. Summary.

This paper studies the present cost C of a renewal process, defined as the sum of the values of the costs of the replacements considered at the starting time of the renewal process, with a compound interest.

The characteristic function of C is found when the inter-arrival times are negatively exponentially distributed; the asymptotic properties of C as the rate of interest tends to zero are studied in the general case.

1. Introduction.

Let us consider a renewal process with inter-arrival times X_1, X_2, \dots identically and independently distributed with distribution function $F(x)$ ($F(0) = 0$). Starting at time $T_0 = 0$ we will have a replacement at each of the instants $T_1 = X_1, T_2 = X_1 + X_2, \dots$.

We suppose that each renewal has a constant cost, which we assume equal to 1. So one will have to pay one (dollar, say) at time T_1 , one at time T_2 , and so on. It is of interest to study the present value, at time 0, of these payments, assuming compound interest.

The present value A_0 , at time 0, of a sum A at time T , is given by:

$$(1) \quad A_0 = e^{-\rho T} A$$

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where ρ is the force of interest (see, for instance, [37]). So the value C_1 , at time 0, of a replacement which will take place at time T_1 , is given by

$$(2) \quad C_1 = e^{-\rho T_1}.$$

The present value, at time 0, of the total cost of the renewal process, which will be denoted by C , is

$$(3) \quad \begin{aligned} C &= \sum_{i=1}^{\infty} C_i \\ &= \sum_{i=1}^{\infty} e^{-\rho \sum_{j=1}^i X_j} \end{aligned}$$

Let us consider the random variables Y_i defined by

$$(4) \quad Y_i = e^{-\rho X_i}.$$

They are independent and identically distributed; we will denote by α_r their moments. If X is a random variable with distribution function $F(x)$, and $\phi_X(t)$ is the characteristic function of X , we have

$$(5) \quad \begin{aligned} \alpha_r &= E Y_j^r \\ &= E e^{-\rho r X} \\ &= \phi_X(i r \rho). \end{aligned}$$

With the exception of the trivial case $P(X = 0) = 1$, we shall have:

$$(6) \quad 0 < \alpha_r < 1.$$

With the introduction of the Y_j , we can write:

$$(7) \quad C = \sum_{i=1}^{\infty} \prod_{j=1}^i Y_j,$$

and the moments of C are easily expressed in terms of the α_r ; putting

$$(8) \quad \gamma_r = E(C^r),$$

we have

$$\begin{aligned} \gamma_1 &= E \sum_{i=1}^{\infty} \prod_{j=1}^i Y_j \\ &= \sum_{i=1}^{\infty} \alpha_1^i \end{aligned}$$

$$(9) \quad = \frac{\alpha_1}{1 - \alpha_1}$$

$$\begin{aligned} \gamma_2 &= E \left(\sum_{i=1}^{\infty} \prod_{j=1}^i Y_j \right)^2 \\ &= 2 E \sum_{i=1}^{\infty} \sum_{k=i+1}^{\infty} \prod_{j=1}^i Y_j \prod_{s=1}^k Y_s + E \sum_{i=1}^{\infty} \left(\prod_{j=1}^i Y_j \right)^2 \\ &= 2 E \sum_{i=1}^{\infty} \sum_{k=i+1}^{\infty} \prod_{j=1}^i Y_j^2 \prod_{j=i+1}^k Y_j + E \sum_{i=1}^{\infty} \prod_{j=1}^i Y_j^2 \\ &= 2 \sum_{i=1}^{\infty} \sum_{k=i+1}^{\infty} \alpha_2^i \alpha_1^{k-i} + \sum_{i=1}^{\infty} \alpha_2^i \\ &= 2 \frac{\alpha_2}{1 - \alpha_2} \frac{\alpha_1}{1 - \alpha_1} + \frac{\alpha_2}{1 - \alpha_2} \\ &= \frac{\alpha_2(1 + \alpha_1)}{(1 - \alpha_2)(1 - \alpha_1)}. \end{aligned}$$

$$(10) \quad \sigma^2(C) = \frac{\alpha_2 - \alpha_1^2}{(1-\alpha_1)^2 (1-\alpha_2)} .$$

The first two moments are finite, because of (6). It can be easily seen that all the moments of C are finite; in fact, as for γ_2 , each moment can be expressed as the sum of a finite number of terms which are all finite. The same result could be obtained by an argument similar to the one used to prove that N_T (i.e. the number of renewals between 0 and T) has finite moments of all orders (see [2], p. 245).

From (3) we obtain moreover

$$(11) \quad C = e^{-\rho X_1} (1 + C')$$

where C' has the same distribution as C , and is independent of X_1 .

2. The case of the negative exponential distribution.

A particular case of great importance in applications is given by the negative exponential distribution, which will be studied in this section. In this case, we have

$$dF(x) = \lambda e^{-\lambda x} dx \quad (x > 0)$$

with $\lambda > 0$. We have also

$$\phi_X(t) = \frac{\lambda}{\lambda - i t} ,$$

$$\alpha_r = \phi_X(i \rho r)$$

$$= \frac{\lambda}{\lambda + r\rho} ,$$

$$EC = \frac{\lambda}{\rho} ,$$

$$\sigma^2(C) = \frac{\lambda}{2\rho} .$$

In order to study the distribution of C , we can use (11). For the characteristic function of C we have

$$\begin{aligned}\phi_C(t) &= E e^{i t C} \\ &= E e^{i t e^{-\rho X_1} + i t e^{-\rho X_1} C'} = E_{X_1} E \left[e^{i t e^{-\rho X} + i t e^{-\rho X} C'} \mid X=X_1 \right] \\ &= E e^{i t e^{-\rho X}} \phi_C(t e^{-\rho X}),\end{aligned}$$

therefore

$$(12) \quad \phi_C(t) = \int_0^{\infty} e^{i t e^{-\rho x}} \phi_C(t e^{-\rho x}) d F(x) .$$

Introducing the density function of the negative exponential distribution, we obtain, by a change of variables:

$$\begin{aligned}\phi_C(t) &= \int_0^{\infty} e^{i t e^{-\rho x}} \phi_C(t e^{-\rho x}) \lambda e^{-\lambda x} dx \\ &= \frac{\lambda}{\rho} \int_0^t e^{i y} \phi_C(y) y^{\frac{\lambda}{\rho} - 1} t^{-\frac{\lambda}{\rho}} dy .\end{aligned}$$

In order to solve this integral equation, we transform it into a differential equation, by differentiating on both sides after multiplying by $t^{\frac{\lambda}{\rho}}$. From

$$t^{\frac{\lambda}{\rho}} \phi_C(t) = \frac{\lambda}{\rho} \int_0^t e^{i y} \phi_C(y) y^{\frac{\lambda}{\rho} - 1} dy$$

we have

$$\frac{\lambda}{\rho} t^{\frac{\lambda}{\rho} - 1} \phi_C(t) + t^{\frac{\lambda}{\rho}} \phi_C'(t) = \frac{\lambda}{\rho} e^{i t} \phi_C(t) t^{\frac{\lambda}{\rho} - 1}$$

and hence

$$\phi'_C(t) = \frac{\lambda}{\rho} \frac{e^{it} - 1}{t} \phi_C(t) ,$$

with the condition

$$\phi_C(0) = 1 .$$

We obtain finally

$$(13) \quad \phi_C(t) = \exp \int_0^t \frac{\lambda}{\rho} \int_0^x \frac{e^{ix} - 1}{x} dx .$$

From this expression we can derive the moments of C ; expanding the exponentials in series, we have

$$\begin{aligned} \phi_C(t) &= \exp \int_0^t \frac{\lambda}{\rho} \int_0^x (1 - \frac{x}{2!} + i \frac{x^2}{3!} - \dots) dx \\ &= \exp \int_0^t \frac{\lambda}{\rho} (i t - \frac{t^2}{4} - \frac{1}{3} \frac{t^3}{3!} + \dots) dt \\ &= 1 + \frac{\lambda}{\rho} (i t - \frac{t^2}{4} - \frac{1}{3} \frac{t^3}{3!} + \dots) \\ &\quad + \frac{1}{2} \frac{\lambda^2}{\rho^2} (i t - \frac{t^2}{4} - \frac{1}{3} \frac{t^3}{3!} + \dots)^2 + \dots \end{aligned}$$

Thus the first moments are

$$\gamma_1 = \frac{\lambda}{\rho} , \quad \gamma_2 = \frac{\lambda}{2\rho} + \frac{\lambda^2}{\rho^2} , \quad \text{i.e. } \sigma^2(C) = \frac{\lambda}{2\rho} .$$

The same results could have been obtained from (9), (10) .

An interesting question concerning the random variable C is its asymptotic behaviour as ρ tends to zero. For the negative exponential distribution the study of this problem is made very easy by formula (13). Let us consider the new

variable Z defined as

$$Z = \frac{C - EC}{\sigma(C)} = \frac{C - \gamma_1}{\sigma}.$$

Using (13) we have

$$\phi_Z(t) = \exp\left[-\frac{\gamma_1}{\sigma} it + \frac{\lambda}{\rho} \int_0^{\frac{t}{\sigma}} \frac{e^{ix} - 1}{x} dx\right].$$

Thus

$$\begin{aligned} \log \phi_Z(t) &= \frac{-\gamma_1}{\sigma} it + \frac{\lambda}{\rho} \left(i \frac{t}{\sigma} - \frac{t^2}{4\sigma^2} - \frac{1}{3} i \frac{t^3}{\sigma^3} + \dots \right) \\ &= -\frac{\lambda}{\rho} \left(\frac{2\rho}{\lambda}\right)^{\frac{1}{2}} t i + \frac{\lambda}{\rho} \left(\frac{2\rho}{\lambda}\right)^{\frac{1}{2}} t i - \frac{\lambda}{\rho} \frac{2\rho}{\lambda} \frac{t^2}{4} - \frac{1}{3} \frac{\lambda}{\rho} \left(\frac{2\rho}{\lambda}\right)^{\frac{3}{2}} \frac{t^3}{3!} + \dots \\ &= -\frac{t^2}{2} - i \frac{2^{\frac{3}{2}}}{3} \lambda^{-\frac{1}{2}} \frac{1}{\rho^{\frac{1}{2}}} \frac{t^3}{3!} + \dots \end{aligned}$$

All the terms in the last expression, except the first one, contain ρ with a positive exponent; the series is uniformly convergent for ρ in any interval of the form $0 \leq \rho \leq \Delta$; hence we have:

$$\lim_{\rho \rightarrow 0} \log \phi_Z(t) = -\frac{t^2}{2}.$$

Thus we have proved:

Theorem 1. If X has a negative exponential distribution, C is asymptotically normally distributed as ρ tends to zero.

3. The general case.

It can be easily seen that the negative exponential distribution is the only one which permits a simple solution of the integral equation (12) by a transformation into a differential equation. In the general case, since the integral equation

(12) is a homogeneous Volterra equation of second kind, the solution must be searched for among the singular solutions. Thus it appears rather difficult to find by this method the distribution of C for distributions of X other than the negative exponential one.

On the other hand, if we want to study the asymptotic properties of the distribution of C , other means are available; for instance, the investigation of the behaviour of the moments of C .

Let us first establish some lemmas.

Lemma 1. If, for an integer k , $\beta_k = E X^k < \infty$, then

$$(14) \quad \alpha_r = 1 - r \beta_1 \rho + \frac{r^2}{2} \beta_2 \rho^2 + \dots + (-1)^k \frac{r^k}{k!} \beta_k \rho^k \theta(\rho)$$

where $0 \leq \theta(\rho) \leq 1$, and $\lim_{\rho \rightarrow 0} \theta(\rho) = 1$.

Proof: We have

$$e^{-r\rho x} = \sum_{i=0}^{k-1} (-1)^i \frac{r^i}{i!} x^i \rho^i + (-1)^k \frac{r^k}{k!} x^k \rho^k \theta_1(x, \rho),$$

where

$$e^{-\rho r x} \leq \theta_1(x, \rho) \leq 1.$$

If we integrate this equation, and use the mean value theorem, then we find

$$\begin{aligned} \int_0^{+\infty} e^{-r\rho x} dF(x) &= \sum_{i=1}^{k-1} (-1)^i \frac{r^i}{i!} \beta_i \rho^i + (-1)^k \frac{r^k}{k!} \rho^k \int_0^{+\infty} x^k \theta_1(x, \rho) dF(x) \\ &= \sum_{i=1}^{k-1} (-1)^i \frac{r^i}{i!} \beta_i \rho^i + (-1)^k \frac{r^k}{k!} \rho^k \beta_k \theta(\rho), \end{aligned}$$

where $0 \leq \theta(\rho) \leq 1$. Moreover

$$\theta(\rho) = \frac{1}{\beta_k} \int_0^{+\infty} x^k \theta_1(x, \rho) dF(x) .$$

Hence it follows from the hypotheses and the properties of $\theta_1(x, \rho)$:

$$\lim_{\rho \rightarrow 0} \theta(\rho) = 1 .$$

The lemma is thus proved.

Lemma 2. If $E X^k < \infty$ ($k \geq 1$) then, for every $t \geq 0$,

$$\lim_{\rho \rightarrow 0} \rho^{-k} E e^{-\rho t X} (e^{-\rho X} - \alpha_1)^h = \begin{cases} E(X - \beta_1)^k & \text{if } h = k \\ 0 & \text{if } h > k \end{cases}$$

Proof: We can write, as in lemma 1,

$$e^{-\rho X} = 1 - \rho x \theta_1(x, \rho) ,$$

where $e^{-\rho X} \leq \theta_1(x, \rho) \leq 1$; and

$$\alpha_1 = 1 - \rho \beta_1 \theta(\rho) ,$$

where $0 \leq \theta(\rho) \leq 1$ and $\lim_{\rho \rightarrow 0} \theta(\rho) = 1$.

Then

$$\begin{aligned} \rho^{-k} E e^{-\rho t X} (e^{-\rho X} - \alpha_1)^h &= E e^{-\rho t X} (e^{-\rho X} - \alpha_1)^{h-k} \left(\frac{e^{-\rho X} - \alpha_1}{\rho} \right)^k \\ &= E e^{-\rho t X} (e^{-\rho X} - \alpha_1)^{h-k} \left[\frac{1 - \rho X \theta_1(x, \rho) - 1 + \rho \beta_1 \theta(\rho)}{\rho} \right]^k \\ &= E e^{-\rho t X} (e^{-\rho X} - \alpha_1)^{h-k} \left[\beta_1 \theta(\rho) - X \theta_1(x, \rho) \right]^k . \end{aligned}$$

Moreover, for $h-k \geq 0$,

$$\begin{aligned} |e^{-\rho t X} (e^{-\rho X} - \alpha_1)^{h-k} [\beta_1 \theta(\rho) - X \theta_1(X, \rho)]^k| &\leq |\beta_1 \theta(\rho) - X \theta_1(X, \rho)|^k \\ &\leq 2^k |\beta_1^k \theta^k(\rho) + X^k \theta_1^k(X, \rho)| \\ &\leq 2^k (\beta_1^k + X^k). \end{aligned}$$

Since the expectation of $2^k (\beta_1^k + X^k)$ is finite, we can interchange the expectation and lim signs, and the lemma is proved.

Let us consider now the central moments $\bar{\gamma}_r$ of C . We have

$$\bar{\gamma}_r = E(C - EC)^r = E(C - \gamma_1)^r$$

From (11) we obtain a recurrence formula for the moments γ_r :

$$\begin{aligned} \gamma_r &= E C^r \\ &= E e^{-r \rho X_1} (1 + C')^r \\ &= E e^{-r \rho X_1} E(1 + C')^r \\ &= \alpha_r E \sum_{j=0}^r \binom{r}{j} C'^j \\ &= \alpha_r \sum_{j=0}^r \binom{r}{j} \gamma_j \end{aligned}$$

By the well-known relations between moments and central moments

$$\begin{aligned} \bar{\gamma}_r &= \sum_{j=0}^r (-1)^{r-j} \binom{r}{j} \gamma_1^{r-j} \gamma_j, \\ \gamma_r &= \sum_{j=0}^r \binom{r}{j} \bar{\gamma}_j \gamma_1^{r-j}, \end{aligned}$$

we may derive a recurrence formula for the central moments of C :

$$\begin{aligned}
\bar{Y}_r &= \sum_{j=0}^r (-1)^{r-j} \binom{r}{j} \gamma_1^{r-j} \gamma_j \\
&= \sum_{j=0}^r (-1)^{r-j} \binom{r}{j} \gamma_1^{r-j} \alpha_j \sum_{t=0}^j \binom{j}{t} \gamma_t \\
&= \sum_{j=0}^r (-1)^{r-j} \binom{r}{j} \gamma_1^{r-j} \alpha_j \sum_{t=0}^j \binom{j}{t} \sum_{i=0}^t \binom{t}{i} \bar{Y}_i \gamma_1^{t-i} \\
&= \sum_{j=0}^r (-1)^{r-j} \binom{r}{j} \gamma_1^{r-j} \alpha_j \sum_{i=0}^j \bar{Y}_i \sum_{t=i}^j \frac{j!}{(j-t)! i! (t-i)!} \gamma_1^{t-i} \\
&= \sum_{j=0}^r (-1)^{r-j} \binom{r}{j} \gamma_1^{r-j} \alpha_j \sum_{i=0}^j \bar{Y}_i \binom{j}{i} (1 + \gamma_1)^{j-i} .
\end{aligned}$$

Substituting γ_1 by (9), we have:

$$\begin{aligned}
\bar{Y}_r &= \sum_{i=0}^r \sum_{j=i}^r (-1)^{r-j} \binom{r}{j} \frac{\alpha_1^{r-j}}{(1-\alpha_1)^{r-j}} \alpha_j \bar{Y}_i \binom{j}{i} \frac{1}{(1-\alpha_1)^{j-i}} \\
&= \sum_{i=0}^r \bar{Y}_i \frac{1}{(1-\alpha_1)^{r-i}} \sum_{j=i}^r (-1)^{r-j} \binom{r}{j} \binom{j}{i} \alpha_1^{r-j} \alpha_j \\
&= \sum_{i=0}^r \binom{r}{i} \frac{1}{(1-\alpha_1)^{r-i}} \bar{Y}_i \sum_{j=i}^r \binom{r-i}{j-i} \alpha_j (-\alpha_1)^{r-j} \\
&= \alpha_r \bar{Y}_r + \sum_{i=0}^{r-1} \binom{r}{i} \frac{1}{(1-\alpha_1)^{r-i}} \bar{Y}_i \sum_{j=i}^r \binom{r-i}{j-i} \alpha_j (-\alpha_1)^{r-j} .
\end{aligned}$$

We obtain finally

$$(15) \quad \bar{Y}_r = \frac{1}{1 - \alpha_r} \sum_{i=0}^{r-1} \binom{r}{i} \frac{1}{(1-\alpha_1)^{r-i}} \bar{Y}_i \sum_{j=i}^r \binom{r-i}{j-i} \alpha_j (-\alpha_1)^{r-j} .$$

Since

$$\begin{aligned} \sum_{j=i}^r \binom{r-i}{j-i} \alpha_j (-\alpha_1)^{r-j} &= \sum_{j=i}^r \binom{r-i}{j-i} E e^{-\rho j X} (-\alpha_1)^{r-j} \\ &= E \sum_{j=i}^r \binom{r-i}{j-i} e^{-\rho j X} (-\alpha_1)^{r-j} \\ &= E e^{-\rho i X} (e^{-\rho X} - \alpha_1)^{r-i}, \end{aligned}$$

(15) can also be written as

$$(15') \quad \bar{\gamma}_r = \frac{1}{1 - \alpha_r} \sum_{i=0}^{r-1} \binom{r}{i} \frac{1}{(1 - \alpha_1)^{r-i}} \bar{\gamma}_i E e^{-\rho i X} (e^{-\rho X} - \alpha_1)^{r-i}.$$

We can now proceed to study the convergence of the central moments $\bar{\gamma}_r$.

Theorem 2. If, for $r > 0$, $E X^{\frac{r}{2} + 1} < \infty$, then

$$(16) \quad \lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} \bar{\gamma}_r = K_r$$

where

$$K_r = \begin{cases} \frac{(\beta_2 - \beta_1^2)^{\frac{r}{2}} r!}{2^r (\frac{r}{2})! \beta_1^{\frac{r}{2}}} & \text{if } r \text{ is even} \\ 0 & \text{if } r \text{ is odd} \end{cases}$$

Proof: We will prove this theorem by induction. Clearly (16) holds for $r = 0, 1$, since $\gamma_0 = 1$, $\gamma_1 = 0$. Now let us assume that it holds for $0, 1, \dots, r-1$, with $r \geq 2$, and prove it must consequently hold for r .

From (15') we have

$$(17) \quad \rho^{\frac{r}{2}} \bar{Y}_r = \sum_{i=1}^{r-1} \rho^{\frac{r}{2}} T_i$$

where

$$\begin{aligned} \rho^{\frac{r}{2}} T_i &= \rho^{\frac{r}{2}} \frac{1}{1-\alpha_r} \frac{1}{(1-\alpha_1)^{r-1}} \binom{r}{i} \bar{Y}_i E e^{-\rho i X} (e^{-\rho X} - \alpha_1)^{r-i} \\ &= \binom{r}{i} \frac{\rho}{1-\alpha_r} \left(\frac{\rho}{1-\alpha_1} \right)^{r-i} \rho^{\frac{i}{2}} \bar{Y}_i \rho^{-\left(\frac{r}{2} + 1 - \frac{i}{2}\right)} E e^{-\rho i X} (e^{-\rho X} - \alpha_1)^{r-i}. \end{aligned}$$

By lemma 1 we obtain:

$$\lim_{\rho \rightarrow 0} \frac{\rho}{1-\alpha_r} = \frac{1}{r \beta_1},$$

so that

$$\lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_i = \binom{r}{i} \frac{1}{r \beta_1} \frac{1}{\beta_1^{r-i}} K_i \lim_{\rho \rightarrow 0} \rho^{-\left(\frac{r}{2} + 1 - \frac{i}{2}\right)} E e^{-\rho i X} (e^{-\rho X} - \alpha_1)^{r-i}.$$

Since $\frac{r}{2} + 1 - \frac{i}{2} \leq \frac{r}{2} + 1$, we have

$$E X^{\frac{r}{2} + 1 - \frac{i}{2}} < \infty$$

and we can use lemma 2. So, if $i < r-2$, we have $\frac{r}{2} + 1 - \frac{i}{2} < r-i$, and then

$$\lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_i = 0.$$

If on the contrary $i = r-2$, i.e. $\frac{r}{2} + 1 - \frac{i}{2} = r-i$, we have:

$$\begin{aligned} \lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_{r-2} &= \binom{r}{2} \frac{1}{r} \frac{1}{\beta_1^3} K_{r-2} E(X - \beta_1)^2 \\ &= \binom{r}{2} \frac{1}{r} \frac{\beta_2 - \beta_1^2}{\beta_1^3} K_{r-2}. \end{aligned}$$

Finally, for $i = r - 1$, we can write

$$E e^{-(r-1)\rho X} (e^{-\rho X} - \alpha_1) = \alpha_r - \alpha_1 \alpha_{r-1}$$

and, by lemma 1, we have

$$\begin{aligned} \lim_{\rho \rightarrow 0} \rho^{-\frac{3}{2}} (\alpha_r - \alpha_1 \alpha_{r-1}) &= \\ &= \lim_{\rho \rightarrow 0} \rho^{-\frac{3}{2}} \left\{ 1 - r\beta_1\rho + o_1(\rho^2) - [1 - (r-1)\beta_1\rho + o_2(\rho^2)] [1 - \beta_1\rho + o_3(\rho^2)] \right\} \\ &= \lim_{\rho \rightarrow 0} \rho^{-\frac{3}{2}} [1 - r\beta_1\rho - 1 + \beta_1\rho + (r-1)\beta_1\rho + o(\rho^2)] \\ &= 0 \end{aligned}$$

Hence

$$\lim_{\rho \rightarrow 0} \rho^{2r} T_{r-1} = 0.$$

We thus have:

$$\begin{aligned} \lim_{\rho \rightarrow 0} \rho^{2r} Y_r &= \sum_{i=0}^{r-1} \lim_{\rho \rightarrow 0} \rho^{2i} T_i \\ &= \binom{r}{2} \frac{1}{r} \frac{\beta_2 - \beta_1^2}{\beta_1^3} K_{r-2}. \end{aligned}$$

If r is odd, so is $r-2$, and then $K_r = K_{r-2} = 0$. If r is even, we have

$$\begin{aligned}
\binom{r}{2} \frac{1}{r} \frac{\beta_2 - \beta_1^2}{\beta_1^3} K_{r-2} &= \binom{r}{2} \frac{1}{r} \frac{\beta_2 - \beta_1^2}{\beta_1^3} \frac{(\beta_2 - \beta_1^2)^{\frac{r}{2} - 1} (r-2)!}{2^{r-2} \left(\frac{r}{2} - 1\right)! \beta_1^{\frac{r}{2} (r-2)}} \\
&= \frac{1}{2^r} \frac{r!}{\binom{r}{2}!} \frac{(\beta_2 - \beta_1^2)^{\frac{r}{2}}}{\beta_1^{\frac{r}{2} r}} = K_r .
\end{aligned}$$

The theorem is thus proved.

Theorem 2 enables us to establish a sufficient condition for the asymptotic normality of C .

Theorem 3. If all the moments of X are finite, then the distribution of $(C - EC)/\sigma(C)$ tends to the standard normal distribution as ρ decreases to zero.

Proof: Theorem 2 gives, for $r = 2$:

$$\lim_{\rho \rightarrow 0} \rho \sigma^2(C) = \frac{\beta_2 - \beta_1^2}{2 \beta_1^3}$$

Thus we have:

$$\begin{aligned}
\lim_{\rho \rightarrow 0} E \left[\frac{C - EC}{\sigma(C)} \right]^r &= \lim_{\rho \rightarrow 0} \frac{\bar{Y}_r}{\sigma^r(C)} \\
&= \lim_{\rho \rightarrow 0} \frac{\rho^{\frac{r}{2}} \bar{Y}_r}{\rho^{\frac{r}{2}} \sigma^r(C)} = \left(\frac{2 \beta_1^3}{\beta_2 - \beta_1^2} \right)^{\frac{r}{2}} K_r \\
&= \frac{1}{2^{\frac{r}{2}}} \frac{r!}{\binom{r}{2}!}
\end{aligned}$$

which is equal to the r -th moment of the normal variate $N(0,1)$. Thus the moments of $(C - EC)/\sigma(C)$ converge to the moments of the normal distribution, and this is sufficient to ensure that the distribution of the variate converge to the normal

distribution (see, for instance, [1] p. 110). The theorem is thus proved.

The asymptotic normality is of course an important feature of C ; it permits us to approximate C with a normal variate when ρ is small. It would be interesting to have some necessary condition in order that the asymptotic distribution be normal; unfortunately a condition of this kind appears rather difficult to establish.

However, the proof given above requires as an essential condition the existence of all the moments of X ; so that one should expect that, if this condition is dropped, the moments of $(C - EC)/\sigma(C)$ do not converge to the moments of the normal variate. That this is actually true will be seen later.

Lemma 3. If $EX < \infty$ and

$$\lim_{\rho \rightarrow 0} \rho^{-t} E (e^{-\rho X} - \alpha_1)^k = 0 \quad (0 < t \leq k)$$

then, for every $q < t$:

$$EX^q < \infty$$

Proof: We will show first that, under the hypotheses above, we have:

$$(18) \quad \lim_{\rho \rightarrow 0} \rho^{-t} E |e^{-\rho X} - \alpha_1|^k = A$$

where $0 \leq A < \infty$. In fact, we can write:

$$(19) \quad \rho^{-t} E (e^{-\rho X} - \alpha_1)^k = \rho^{-t} \int_0^{-\frac{1}{\rho} \log \alpha_1} (e^{-\rho x} - \alpha_1)^k dF(x) + \rho^{-t} \int_{-\frac{1}{\rho} \log \alpha_1}^{+\infty} (e^{-\rho x} - \alpha_1)^k dF(x)$$

Now, since $\beta_1 = E X < \infty$,

$$\begin{aligned} \lim_{\rho \rightarrow 0} \left(-\frac{1}{\rho} \log \alpha_1 \right) &= - \lim_{\rho \rightarrow 0} \frac{1}{\alpha_1} \frac{d \alpha_1}{d \rho} \\ &= \lim_{\rho \rightarrow 0} \frac{\int_0^{+\infty} x e^{-\rho x} dF(x)}{\int_0^{+\infty} e^{-\rho x} dF(x)} \\ &= \beta_1 \end{aligned}$$

Moreover

$$\begin{aligned} \rho^{-t} |e^{-\rho x} - \alpha_1|^k &= |e^{-\rho x} - \alpha_1|^{k-t} |\beta_1 e(\rho) - x e_1(x, \rho)|^t \\ &\leq 2^t (\beta_1^t + x^t). \end{aligned}$$

Hence

$$\lim_{\rho \rightarrow 0} \rho^{-t} \int_0^{\frac{1}{\rho} \log \alpha_1} (e^{-\rho x} - \alpha_1)^k dF(x) = \frac{A}{2},$$

where

$$\frac{A}{2} = \begin{cases} \int_0^{\beta_1} (\beta_1 - x)^t dF(x) & \text{if } k = t \\ 0 & \text{if } k > t. \end{cases}$$

Since, by hypothesis, the left side of (19) tends to zero, we have also

$$\lim_{\rho \rightarrow 0} \rho^{-t} \int_{-\frac{1}{\rho} \log \alpha_1}^{+\infty} (e^{-\rho x} - \alpha_1)^k dF(x) = -\frac{A}{2}.$$

We have finally

$$\rho^{-t} E|e^{-\rho X} - \alpha_1|^k = \rho^{-t} \left| \int_0^{\frac{1}{\rho} \log \alpha_1} (e^{-\rho x} - \alpha_1)^k dF(x) + \rho^{-t} \int_{\frac{1}{\rho} \log \alpha_1}^{\infty} (e^{-\rho x} - \alpha_1)^k dF(x) \right|, \quad 18$$

$$- \frac{1}{\rho} \log \alpha_1$$

and (18) follows.

Now, since $\lim_{\rho \rightarrow 0} \alpha_1 = 1$, given a number K with $0 < K < 1$, by making ρ small enough, we can make $\alpha_1 > K$. Then we have:

$$E|e^{-\rho X} - \alpha_1|^k \geq \int_{\frac{1}{\rho} \log \frac{1}{K}}^{\infty} (\alpha_1 - e^{-\rho x})^k dF(x)$$

$$\geq (\alpha_1 - K)^k \int_{\frac{1}{\rho} \log \frac{1}{K}}^{\infty} dF(x)$$

$$= (\alpha_1 - K)^k [1 - F(\frac{1}{\rho} \log \frac{1}{K})].$$

If we put $\frac{1}{\rho} \log \frac{1}{K} = x$, we obtain

$$x^t [1 - F(x)] = (\log \frac{1}{K})^t \rho^{-t} [1 - F(\frac{1}{\rho} \log \frac{1}{K})]$$

$$\leq \frac{(\log \frac{1}{K})^t}{(\alpha_1 - K)^k} \rho^{-t} E|e^{-\rho X} - \alpha_1|^k.$$

Then from (18) it follows that

$$\overline{\lim}_{x \rightarrow \infty} x^t [1 - F(x)] \leq (\log \frac{1}{K})^t (1 - K)^{-k} A.$$

This establishes the lemma.

Theorem 4. If $E X^2 < \infty$, then in order that all the moments of $(C - EC)/\sigma(C)$ converge to the moments of the normal distribution $N(0,1)$, it is necessary that all the moments of X be finite.

Proof: The proof will be by induction. Since $E X^2 < \infty$, the convergence of $E[(C - EC)/\sigma(C)]^k$ to the k -th central moment of the normal variate $N(0,1)$ is equivalent to

$$(20) \quad \lim_{\rho \rightarrow 0} \rho^{\frac{k}{2}} \bar{\gamma}_k = K_k$$

We will assume that $E X^{\frac{r}{2}} < \infty$ for an integer $r \geq 4$, and that (20)

holds for every integer k , and we will prove that

$E X^{\frac{r+1}{2}} < \infty$. The theorem will thus be proved.

With the notation of theorem 2, (17) holds; since (20) holds for $k < r$, we have again:

$$\lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_i = \binom{r}{i} \frac{1}{r \beta_1} \frac{1}{\beta_1^{r-i}} K_i \lim_{\rho \rightarrow 0} \rho^{-(\frac{r}{2} + 1 - \frac{i}{2})} E e^{-\rho i X} (e^{-\rho X} - \alpha_1)^{r-i}.$$

For $i \geq 2$, that is $\frac{r}{2} + 1 - \frac{i}{2} \leq \frac{r}{2}$, we have $E X^{\frac{r}{2} + 1 - \frac{i}{2}} < \infty$.

Hence, for $i \geq 2$, the conclusions of theorem 2 hold, that is

$$\lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_i = \begin{cases} K_r & \text{if } i = r-2 \\ 0 & \text{if } i \neq r-2 \end{cases}$$

Moreover, for $i = 1$, $\gamma_1 = 0$; thus

$$\lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} \bar{\gamma}_r = \sum_{i=0}^{r-1} \lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_i = K_r + \lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} T_0.$$

Since (20) holds for $k = r$, the last limit above must be zero, that is:

$$\lim_{\rho \rightarrow 0} \rho^{\frac{r}{2}} \frac{1}{1 - \alpha_r} \frac{1}{(1 - \alpha_1)^r} E(e^{-\rho X} - \alpha_1)^r = 0.$$

$$\lim_{\rho \rightarrow 0} \rho^{-\left(\frac{r}{2} + 1\right)} E(e^{-\rho X} - \alpha_1)^r = 0.$$

By lemma 3, this implies that $E X^q < \infty$ for every $q < \frac{r}{2} + 1$, in particular for $q = \frac{r+1}{2}$. The theorem is thus proved.

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