

Fixed Income and Credit Risk : solutions for exercise sheet n° 04

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Professor	Assistant	Program
Fulvio Pegoraro	Roberto Marfè	MSc. Finance

Exercise N° 01 [Exponential-affine ZCB Pricing Formula].

Given that $M_{t,t+1}$ is exponential-affine in ε_{t+1} (i.e. x_{t+1}) and that the conditional Laplace transform of x_{t+1} is exponential-affine in the conditioning variable (x_t) we suggest that the ZCB pricing formula at date t be an exponential-affine function of x_t and then “we check if it works”. We proceed in the following way:

- a) We suggest $B(t, t+h) = \exp(c'_h X_t + d_h)$ and we (equivalently) rewrite the pricing formula in terms of the payoff $B(t+1, t+h) = \exp(c'_{h-1} X_{t+1} + d_{h-1})$:

$$\begin{aligned}
 B(t, t+h) &= \exp(c'_h X_t + d_h) \\
 &= E_t[M_{t,t+1} \cdots M_{t+h-1,t+h}] \\
 &= E_t[M_{t,t+1} B(t+1, t+h)] \\
 &= E_t \left[\exp \left(-\beta - \alpha' X_t + \Gamma_t \varepsilon_{t+1} - \frac{1}{2} \Gamma_t^2 \right) \exp(c'_{h-1} X_{t+1} + d_{h-1}) \right],
 \end{aligned}$$

- b) we do the algebra (calculating the conditional Laplace transform) obtaining:

$$\begin{aligned}
 &B(t, t+h) \\
 &= \exp(c'_h X_t + d_h) \\
 &= \exp \left[-\beta - \alpha' X_t - \frac{1}{2} \Gamma_t^2 + d_{h-1} \right] \times E_t \left[\exp \left(\Gamma_t \varepsilon_{t+1} + c'_{h-1} X_{t+1} \right) \right] \\
 &= \exp \left[-\beta - \alpha' X_t - \frac{1}{2} \Gamma_t^2 + d_{h-1} + c'_{h-1} (\Phi X_t + \tilde{\nu}) \right] \times E_t \left[\exp \left(\Gamma_t + \sigma c_{1,h-1} \right) \varepsilon_{t+1} \right] \\
 &= \exp \left[(-\alpha + \Phi' c_{h-1} + c_{1,h-1} \sigma \gamma)' X_t \right. \\
 &\quad \left. + (-\beta + c_{1,h-1} \nu + \frac{1}{2} c_{1,h-1}^2 \sigma^2 + \gamma_o c_{1,h-1} \sigma + d_{h-1}) \right],
 \end{aligned}$$

- c) and by identifying the coefficients we find the recursive relations for c_h and d_h characterizing the pricing formula $B(t, t+h) = \exp(c'_h X_t + d_h)$.

Now, the last elements we need to completely determine the pricing formula are the starting conditions for c_h and d_h . We proceed as follows:

given that, by definition of ZCB, we have $B(t, t) = 1$, then

$$\exp(c'_0 X_t + d_0) = 1 \iff (c'_0 X_t + d_0) = 0 \quad \forall X_t \iff c_0 = 0, \quad d_0 = 0.$$

We can also equivalently write:

given that, by definition of ZCB, we have $B(t, t+1) = \exp(-r_t)$, then

$$\exp(c'_1 X_t + d_1) = \exp(-r_t) \iff (c'_1 X_t + d_1) = -r_t \quad \forall X_t \iff c_1 = -\alpha, \quad d_1 = -\beta.$$

Exercise N° 02 [Identification Issue in latent factor Gaussian ATSMs].

We have the following family of Gaussian AR(p) Factor-Based term structure models:

$$\begin{aligned} x_{t+1} &= \nu + \varphi x_t + \sigma \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, 1) \quad (\text{under } \mathbb{P}) \\ M_{t,t+1} &= \exp \left[-\beta - \alpha x_t + \Gamma_t \varepsilon_{t+1} - \frac{1}{2} \Gamma_t^2 \right], \quad (\text{SDF}) \\ r_t &= \beta + \alpha x_t, \quad \Gamma_t = \Gamma(x_t) = (\gamma_o + \gamma x_t), \\ R(t, h) &= -\frac{c_h}{h} x_t - \frac{d_h}{h}, \\ c_h &= -\alpha + \varphi c_{h-1} + c_{h-1} \sigma \gamma = -\alpha + (\varphi + \sigma \gamma) c_{h-1}, \\ d_h &= -\beta + c_{h-1} (\nu + \gamma_o \sigma) + \frac{1}{2} c_{h-1}^2 \sigma^2 + d_{h-1}, \\ c_0 &= 0, \quad d_0 = 0. \end{aligned}$$

We have seen that the yield-to-maturity formula $R(t, h)$ is completely determined by the specification of the historical dynamics of x_{t+1} (Gaussian AR(1)) and by the specification of the one-period SDF $M_{t,t+1}$ (exponential-affine in ε_{t+1}). The identification issue, associated to the specification of yield-to-maturity formula, is therefore given by the fact that different (infinitely many) set of parameter values (ν, φ, σ) and $(\beta, \alpha, \gamma_o, \gamma)$ can generate the same theoretical $R(t, h)$. This means that, from a given time series of observations $R^o(t, h)$, we cannot detect the unique set of parameters such that the distance between $R(t, h)$ and $R^o(t, h)$ is minimized, given that several different set of parameters determine the same $R(t, h)$.

More formally : for arbitrary real constants μ_1 and μ_2 , if we replace:

- a) x_t by $\bar{x}_t = \mu_1 + \mu_2 x_t$ (any Gaussian stochastic process can be represented as an affine transformation of the centered and normalized one),
- b.1) γ by $\frac{\gamma}{\mu_2}$,

$$b.2) \quad \gamma_o \text{ by } \gamma_o - \frac{\mu_1}{\mu_2} \gamma' e,$$

$$b.3) \quad \alpha \text{ by } \frac{\alpha}{\mu_2}$$

$$b.4) \quad \text{and } \beta \text{ by } \beta - \frac{\mu_1}{\mu_2} \alpha' e.$$

we obtained the same SDF $M_{t,t+1}$ dynamics (depending on the factor dynamics) and therefore we generate the same yield $R(t, h)$ (remember that $B(t, h) = E_t[M_{t,t+1} \dots M_{t+h-1,t+h}]$). In other words, for a starting parametric specification of x_t and $M_{t,t+1} = M_{t,t+1}(x_t)$, we have that, after the parametric transformations $a)$, $b.1) - b.4)$, we obtain a new latent factor \bar{x}_t and SDF $\bar{M}_{t,t+1}(\bar{x}_t)$ such that $M_{t,t+1}(x_t) = M_{t,t+1}(\bar{x}_t)$ for any t . Thus, $E_t[M_{t,t+1} \dots M_{t+h-1,t+h}] = E_t[\bar{M}_{t,t+1} \dots \bar{M}_{t+h-1,t+h}]$ for any t and h and the theoretical yields are therefore the same.

If x_t is not directly observed, we can assume for instance, as far as the term structure is concerned, that $\nu = 0$ and $\sigma = 1$, or $\beta = 0$ and $\alpha = 1$. In this way the identification problem is solved. This result is easily generalized to the case of a Gaussian AR(p) process [see Monfort and Pegoraro (2007), Section 2.4].

Exercise N° 03 [Excess Returns of Zero-Coupon Bonds].

Given that $B(t, T) = \exp(c'_{T-t} X_t + d_{T-t})$, we can write:

$$\begin{aligned} \rho(t+1, T) &= \log[B(t+1, T)] - \log[B(t, T)] \\ &= c'_{T-t-1} X_{t+1} + d_{T-t-1} - c'_{T-t} X_t - d_{T-t} \\ &= c'_{T-t-1} [X_{t+1} - \Phi X_t - \tilde{\nu}] + (\beta + \alpha' X_t) - \sigma c_{1,T-t-1} (\gamma_o + \gamma' X_t) - \frac{1}{2} c_{1,T-t-1}^2 \sigma^2 \\ &= (c_{1,T-t-1} \sigma) \varepsilon_{t+1} + (\beta + \alpha' X_t) - \sigma c_{1,T-t-1} (\gamma_o + \gamma' X_t) - \frac{1}{2} c_{1,T-t-1}^2 \sigma^2. \end{aligned}$$

Now, we have that, under the absence of arbitrage $r_t = (\beta + \alpha' X_t)$ and, consequently, the result is proved.

Exercise N° 04 [Risk-Neutral Laplace Transform of the Gaussian AR(p) Factor].

The risk-neutral Laplace transform of x_{t+1} , conditionally to \underline{x}_t , is given by:

$$\begin{aligned} E_t^{\mathbb{Q}}[\exp(ux_{t+1})] &= E_t \left[\frac{M_{t,t+1}}{E_t(M_{t,t+1})} \exp(ux_{t+1}) \right] \\ &= E_t \left[\exp((\gamma_o + \gamma' X_t) \varepsilon_{t+1} - \frac{1}{2} (\gamma_o + \gamma' X_t)^2 + ux_{t+1}) \right] \\ &= \exp \left[u(\nu + \varphi' X_t) - \frac{1}{2} (\gamma_o + \gamma' X_t)^2 \right] \\ &\quad E_t[\exp((\gamma_o + \gamma' X_t + u\sigma) \varepsilon_{t+1})] \\ &= \exp \left[u[(\nu + \sigma\gamma_o) + (\varphi + \sigma\gamma)' X_t] + \frac{1}{2} u^2 \sigma^2 \right], \end{aligned}$$

where $\varphi = [\varphi_1, \dots, \varphi_p]'$.

Exercise N° 05 [Risk-Neutral Zero-Coupon Bond Return Process].

We have that

$$\begin{aligned}
\rho(t+1, T) &= \log[B(t+1, T)] - \log[B(t, T)] \\
&= c'_{T-t-1}X_{t+1} + d_{T-t-1} - c'_{T-t}X_t - d_{T-t} \\
&= c'_{T-t-1}X_{t+1} - (-\alpha' + c'_{T-t-1}\Phi^*)X_t + \beta - c_{1,T-t-1}\nu^* - \frac{1}{2}c_{1,T-t-1}^2\sigma^2 \\
&= c'_{T-t-1}[X_{t+1} - \Phi^*X_t - \tilde{\nu}^*] + r_t - \frac{1}{2}c_{1,T-t-1}^2\sigma^2 \\
&= r_t - \frac{1}{2}\omega(t+1, T)^2 - \omega(t+1, T)\eta_{t+1}
\end{aligned}$$

and the first part of the result is proved. Now, if we calculate $E_t^{\mathbb{Q}} \exp[\rho(t+1, T)]$ we have:

$$\begin{aligned}
E_t^{\mathbb{Q}} \exp[\rho(t+1, T)] &= E_t^{\mathbb{Q}} \exp[r_t - \frac{1}{2}\omega(t+1, T)^2 - \omega(t+1, T)\eta_{t+1}] \\
&= \exp[r_t - \frac{1}{2}\omega(t+1, T)^2] E_t^{\mathbb{Q}} \exp[-\omega(t+1, T)\eta_{t+1}] = \exp(r_t)
\end{aligned}$$

and therefore $\lambda_t^{\mathbb{Q}}(\rho, 1) = \log E_t^{\mathbb{Q}} \exp[\rho(t+1, T)] - r_t = 0$.

Exercise N° 06 [Yield Curve Shapes, Risk-Neutral Stationarity and Long Rates].

The different shapes that the yield curve formula $R(t, t+h) = -\frac{1}{h}[c'_h X_t + d_h]$ is able to reproduce depend crucially on the system of difference equations (c_h, d_h) :

$$\begin{cases} c_h &= \Phi^* c_{h-1} - \alpha \\ d_h &= -\beta + c_{1,h-1}\nu^* + \frac{1}{2}c_{1,h-1}^2\sigma^2 + d_{h-1}, \end{cases}$$

with initial conditions $c_0 = 0$ and $d_0 = 0$. Let us consider in that exercise the case where x_{t+1} follows a Gaussian AR(1) and AR(2) process respectively.

$p = 1$ Let us consider that $x_t = r_t$ follows a Gaussian AR(1) process. In this case c_h satisfies the first-order difference equation:

$$c_h = -1 + (\varphi + \sigma\gamma)c_{h-1},$$

where $\sigma > 0$, γ and $|\varphi| < 1$ are scalar coefficients, and with a general solution, denoted $c(h)$, given by:

$$c(h) = -\left[\frac{1}{1 - (\varphi + \sigma\gamma)}\right] [1 - (\varphi + \sigma\gamma)^h] = -\left[\frac{1 - \varphi^{*h}}{1 - \varphi^*}\right],$$

which tends, for h increasing to infinity, to the limit:

$$\bar{c} = - \left[\frac{1}{1 - \varphi^*} \right],$$

under the condition $|\varphi^*| < 1$, where $\varphi^* = (\varphi + \sigma\gamma)$ is the unique eigenvalue of the (scalar) matrix $\Phi^{*'}.$ This means that this stability condition of the difference equation c_h coincide with the stationarity condition of the AR(1) process x_{t+1} under the risk-neutral probability $\mathbb{Q}.$

Now, observe that this condition implies $c(h) < 0$ for every $h > 0.$ In addition, if $0 < \varphi + \sigma\gamma < 1$ (respectively, $-1 < \varphi + \sigma\gamma < 0$), the function $c(h)$ converges in decreasing (respectively, oscillating) towards $\bar{c}.$

With regard to $d_h,$ it easy to verify that :

$$\begin{aligned} d(h) = & - \left[\frac{\nu^*}{1 - \varphi^*} \right] (h - 1) + \left[\frac{\varphi^* - \varphi^{*h}}{1 - \varphi^*} \right] \left[\frac{\nu^*}{1 - \varphi^*} - \frac{\sigma^2}{(1 - \varphi^*)^2} \right] \\ & + \frac{\sigma^2}{2(1 - \varphi^*)^2} \left[(h - 1) + \frac{\varphi^{*2} - \varphi^{*2h}}{1 - \varphi^{*2}} \right]. \end{aligned}$$

Consequently, the yield to maturity formula, for $p = 1,$ is given by :

$$\begin{aligned} R(t, t + h) = & \frac{1}{h} \left[\frac{1 - \varphi^{*h}}{1 - \varphi^*} \right] r_t + \frac{(h - 1)}{h} \left[\frac{\nu^*}{1 - \varphi^*} \right] - \frac{1}{h} \left[\frac{\varphi^* - \varphi^{*h}}{1 - \varphi^*} \right] \left[\frac{\nu^*}{1 - \varphi^*} - \frac{\sigma^2}{(1 - \varphi^*)^2} \right] \\ & - \frac{\sigma^2}{2h(1 - \varphi^*)^2} \left[(h - 1) + \frac{\varphi^{*2} - \varphi^{*2h}}{1 - \varphi^{*2}} \right]. \end{aligned}$$

$p = 2$ If the factor $x_t = r_t$ is a Gaussian AR(2) process, the recursive equation for c_h is described by a first-order (2×2) system of difference equations of the following type:

$$\begin{bmatrix} c_{1,h} \\ c_{2,h} \end{bmatrix} - \begin{bmatrix} \varphi_1 + \sigma\gamma_1 & 1 \\ \varphi_2 + \sigma\gamma_2 & 0 \end{bmatrix} \begin{bmatrix} c_{1,h-1} \\ c_{2,h-1} \end{bmatrix} = - \begin{bmatrix} 1 \\ 0 \end{bmatrix} ; \quad (1)$$

substituting the first equation into the second, we find for $c_{1,h+1}$ the following second-order linear difference equation:

$$c_{1,h+1} = -1 + \varphi_1^* c_{1,h} + \varphi_2^* c_{1,h-1}, \quad (2)$$

where $\varphi_1^* = (\varphi_1 + \sigma\gamma_1)$ and $\varphi_2^* = (\varphi_1 + \sigma\gamma_2);$ under the condition that the two eigenvalues (λ_1, λ_2) of $\Phi^{*'} ($ or the inverse of the roots of $1 - \varphi_1^* L - \varphi_2^* L^2)$ are not equal and less than unity in modulus, and regardless of their real or complex nature, the limit of $c_{1,h}$ is given by:

$$\bar{c}_1 = - \frac{1}{(1 - \lambda_1)(1 - \lambda_2)} ;$$

these conditions can equivalently be expressed in the following way : $\varphi_1^* + \varphi_2^* < 1,$ $\varphi_2^* - \varphi_1^* < 1$ and $|\varphi_2^*| < 1.$ These are exactly the stationarity conditions of the Gaussian AR(2) process x_{t+1} under the risk-neutral probability $\mathbb{Q}.$

If we substitute \bar{c}_1 into the second equation of system (1) we find, consequently, the limit of $c_{2,h}$:

$$\bar{c}_2 = -\varphi_2^* \frac{1}{(1-\lambda_1)(1-\lambda_2)}.$$

The recursive equation characterizing d_h is given by:

$$d_h = \begin{cases} 0 & \text{for } h = 1, \\ \nu^* \sum_{j=1}^{h-1} c_j + \frac{1}{2} \sigma^2 \sum_{j=1}^{h-1} c_j^2, & \forall h \geq 2, \end{cases}$$

that is, it is a function of (some parameter and) c_j for $j \in \{1, \dots, h-1\}$.

Exercise N° 07.

Let us consider again the system of difference equations (c_h, d_h) :

$$\begin{cases} c_h &= \Phi^{*'} c_{h-1} - \alpha \\ d_h &= -\beta + c_{1,h-1} \nu^* + \frac{1}{2} c_{1,h-1}^2 \sigma^2 + d_{h-1}, \end{cases}$$

with initial conditions $c_0 = 0$ and $d_0 = 0$. Let us consider in that exercise the general case where x_{t+1} follows a Gaussian AR(p) process. In this case, it is well known that the steady state $\bar{\mathbf{C}} = [\bar{c}_1, \dots, \bar{c}_p]'$ of the system c_h is given, I denoting the $(p \times p)$ identity matrix, by:

$$\bar{\mathbf{C}} = -(I - \Phi^{*'})^{-1} \alpha, \quad (3)$$

under the (stability) condition that the p eigenvalues $(\lambda_1, \dots, \lambda_p)$ of $\Phi^{*'}$ are all smaller than unity in modulus, or, equivalently, that the risk-neutral dynamics of (x_t) is stationary, or that the roots of the risk-neutral autoregressive polynomial (of degree p) $\Psi^*(L) = 1 - \varphi_1^* L - \dots - \varphi_p^* L^p$ have a modulus larger than one (given that these roots are the inverse of the eigenvalues). More precisely, the system of equations c_h can be rewritten as:

$$\begin{cases} c_{1,h} &= \varphi_1^* c_{1,h-1} + c_{2,h-1} - \alpha_1 \\ c_{2,h} &= \varphi_2^* c_{1,h-1} + c_{3,h-1} - \alpha_2 \\ &\vdots \\ c_{p-1,h} &= \varphi_{p-1}^* c_{1,h-1} + c_{p,h-1} - \alpha_{p-1} \\ c_{p,h} &= \varphi_p^* c_{1,h-1} - \alpha_p, \end{cases}$$

and if we substitute the p^{th} equation in the $(p-1)^{th}$ for $c_{p,h-1}$, and then the $(p-1)^{th}$ equation in the $(p-2)^{th}$ for $c_{p-1,h-1}$, and so on till the first one, we find that $c_{1,h}$ is described by the following p^{th} order linear difference equation :

$$\Psi^*(L) c_{1,h} = - \sum_{i=1}^p \alpha_i,$$

where $\Psi^*(L) = 1 - \varphi_1^*L - \dots - \varphi_p^*L^p$ operates here to h . The remaining equations are given by :

$$c_{p-j,h} = - \sum_{i=0}^j \alpha_{p-i} + \sum_{i=0}^j \varphi_{p-i}^* c_{1,h-j+i-1}, \quad j \in \{0, \dots, p-2\}.$$

Given the risk-neutral stationary assumption on the process (x_t) , the relations $c_{p-j,h}$, for $j \in \{0, \dots, p-1\}$, converge at an exponential rate with possible oscillations, when $h \rightarrow \infty$. The limits are :

$$\begin{aligned} \bar{c}_1 &= - \frac{\sum_{i=1}^p \alpha_i}{\Psi^*(1)}, \\ \bar{c}_{p-j} &= - \sum_{i=0}^j \alpha_{p-i} + \bar{c}_1 \sum_{i=0}^j \varphi_{p-i}^*, \quad j \in \{0, \dots, p-2\}. \end{aligned}$$

Note that $\Psi^*(1) > 0$ because of the stability conditions.

With regard to d_h , its equation gives the specification of the long-term yield $R(t, \infty)$ as a function of the steady state \bar{c}_1 . Indeed, the difference equation d_h can be written (assuming the identification condition $\beta = 0$, as we have seen in Exercise N° 02) as:

$$d_h = \begin{cases} 0 & \text{for } h = 1, \\ \nu^* \sum_{j=1}^{h-1} c_{1,j} + \frac{1}{2} \sigma^2 \sum_{j=1}^{h-1} c_{1,j}^2, & \forall h \geq 2, \end{cases} \quad (4)$$

and, under the stability of the system c_h , we have from the yield-to-maturity formula that:

$$\begin{aligned} R(t, \infty) &= \lim_{h \rightarrow +\infty} R(t, h) \\ &= \lim_{h \rightarrow +\infty} -\frac{c_h'}{h} X_t - \frac{\nu^*}{h} \sum_{j=1}^{h-1} c_{1,j} - \frac{\sigma^2}{2h} \sum_{j=1}^{h-1} c_{1,j}^2 = -\bar{c}_1 \nu^* - \frac{1}{2} (\bar{c}_1 \sigma)^2, \end{aligned}$$

which is positive under the condition $[\nu^* + \frac{1}{2} \sigma^2 \bar{c}_1] > 0$.

The shape of c_h (and thus the yield curve shapes), for h varying, depends on whether the eigenvalues $(\lambda_1, \dots, \lambda_p)$ of $\Phi^{*'}$ are real or complex, single or multiple, larger or smaller than one in modulus.

Exercise N° 08 [Gaussian AR(p) Factor Dynamics under the S -Forward probability].

The S -forward Laplace transform of x_{t+1} , conditionally to $I_t = (x_t)$, can be written in the following way:

$$\begin{aligned} & E_t^{\mathbb{Q}^{(S)}} [\exp(ux_{t+1})] \\ &= \frac{1}{B(t, S)} E_t^{\mathbb{Q}} [\exp(-r_t - \dots - r_{S-1} + ux_{t+1})]. \end{aligned} \quad (5)$$

Now, starting from the identity

$$\log[B(t, T)] = \sum_{j=1}^t \rho(j, T) + \log[B(0, T)], \quad (6)$$

we have in the risk-neutral world:

$$\log[B(t, T)] = -\sum_{j=1}^t \omega(j, T)\eta_j + \sum_{j=1}^t r_{j-1} - \frac{1}{2} \sum_{j=1}^t \omega(j, T)^2 + \log[B(0, T)]. \quad (7)$$

If we put $T = t$ in (7), we get a relation for the sum of the short-rates:

$$\sum_{j=1}^t r_{j-1} = \sum_{j=1}^t \omega(j, t)\eta_j + \frac{1}{2} \sum_{j=1}^t \omega(j, t)^2 - \log[B(0, t)], \quad (8)$$

that we can substitute in (7) to find the following alternative representation for the bond price process:

Proposition : For every fixed maturity T , the zero-coupon bond price process $B(\cdot, T) = [B(t, T), 0 \leq t \leq T]$, under the risk-neutral probability \mathbb{Q} , can be written as :

$$B(t, T) = \frac{B(0, T)}{B(0, t)} \exp\left(-\sum_{j=1}^t [\omega(j, T) - \omega(j, t)] \eta_j - \frac{1}{2} \sum_{j=1}^t [\omega(j, T)^2 - \omega(j, t)^2]\right). \quad (9)$$

From relation (8), we have that, under the risk-neutral measure \mathbb{Q} , the sum of short-term rates in the above formula can be written as:

$$\begin{aligned} \sum_{j=t+1}^S r_{j-1} &= \sum_{j=1}^S r_{j-1} - \sum_{j=1}^t r_{j-1} \\ &= \sum_{j=1}^S \omega(j, S)\eta_j - \sum_{j=1}^t \omega(j, t)\eta_j \\ &\quad + \frac{1}{2} \left[\sum_{j=1}^S \omega(j, S)^2 - \sum_{j=1}^t \omega(j, t)^2 \right] + \log \left[\frac{B(0, t)}{B(0, S)} \right] \end{aligned}$$

and, consequently, we get:

$$\begin{aligned}
& E_t^{\mathbb{Q}^{(S)}} [\exp(ux_{t+1})] \\
&= \frac{\exp \left[-\frac{1}{2} \left[\sum_{j=1}^S \omega(j, S)^2 - \sum_{j=1}^t \omega(j, t)^2 \right] - \sum_{j=1}^t [\omega(j, S) - \omega(j, t)] \eta_j - \log \left[\frac{B(0, t)}{B(0, S)} \right] \right]}{B(t, S)} \times \\
& E_t^{\mathbb{Q}} \left[\exp \left(- \sum_{j=t+2}^S \omega(j, S) \eta_j - \omega(t+1, S) \eta_{t+1} + u[\nu^* + \varphi^{*'} X_t + \sigma^* \eta_{t+1}] \right) \right] \\
&= k_{t, S} E_t^{\mathbb{Q}} \left[\exp \left(- \sum_{j=t+2}^S \omega(j, S) \eta_j \right) \right] \times \\
& E_t^{\mathbb{Q}} \left[\exp \left(u(\nu^* + \varphi^{*'} X_t) + (u\sigma^* - \omega(t+1, S)) \eta_{t+1} \right) \right] \\
&= k'_{t, S} \exp \left[u \left[\nu^* + \varphi^{*'} X_t - \sigma^* \omega(t+1, S) \right] + \frac{1}{2} u^2 \sigma^{*2} \right]; \tag{10}
\end{aligned}$$

now, using (9) we have that

$$\begin{aligned}
k_{t, S} &= \frac{\exp \left[-\frac{1}{2} \left[\sum_{j=1}^S \omega(j, S)^2 - \sum_{j=1}^t \omega(j, t)^2 \right] - \sum_{j=1}^t [\omega(j, S) - \omega(j, t)] \eta_j - \log \left[\frac{B(0, t)}{B(0, S)} \right] \right]}{B(t, S)} \\
&= \exp \left[-\frac{1}{2} \sum_{j=t+1}^S \omega(j, S)^2 \right]
\end{aligned}$$

and that

$$k'_{t, S} = k_{t, S} \exp \left[\frac{1}{2} \sum_{j=t+1}^S \omega(j, S)^2 \right] = 1.$$

Consequently, we recognize the conditional Laplace transform of the following Gaussian AR(p) stochastic process:

$$x_{t+1} = \nu_S + \varphi_1^* x_t + \dots + \varphi_p^* x_{t+1-p} + \sigma^* \xi_{t+1},$$

with

$$\nu_S = \nu^* - \sigma^* \omega(t+1, S),$$

and where $\xi_{t+1} \sim \mathcal{IIN}(0, 1)$ under \mathbb{Q}_S .

Exercise N° 09 [Zero-Coupon Bond Return Process under the S -Forward probability].

We have that:

$$\begin{aligned}
 \rho(t+1, T) &= \log [B(t+1, T)] - \log [B(t, T)] \\
 &= c'_{T-t-1} X_{t+1} + d_{T-t-1} - c'_{T-t} X_t - d_{T-t} \\
 &= c'_{T-t-1} [X_{t+1} - \Phi^* X_t - \tilde{\nu}^*] + r_t - \frac{1}{2} c_{1, T-t-1}^2 \sigma^{*2} \\
 &= c'_{T-t-1} \left[\sigma^* \left(\tilde{\xi}_{t+1} - \omega(t+1, S) e_1 \right) \right] + r_t - \frac{1}{2} c_{1, T-t-1}^2 \sigma^{*2} \\
 &= r_t + \omega(t+1, T) \omega(t+1, S) \\
 &\quad - \frac{1}{2} \omega(t+1, T)^2 - \omega(t+1, T) \xi_{t+1},
 \end{aligned}$$

and the first part of the result is proved. Now, if we calculate $E_t^{\mathbb{Q}^{(S)}} \{ \exp [\rho(t+1, T)] \}$ we have:

$$\begin{aligned}
 E_t^{\mathbb{Q}^{(S)}} \exp [\rho(t+1, T)] &= E_t^{\mathbb{Q}^{(S)}} \exp \left[r_t + \omega(t+1, T) \omega(t+1, S) - \frac{1}{2} \omega(t+1, T)^2 - \omega(t+1, T) \xi_{t+1} \right] \\
 &= \exp \left[r_t + \omega(t+1, T) \omega(t+1, S) - \frac{1}{2} \omega(t+1, T)^2 \right] E_t^{\mathbb{Q}^{(S)}} \exp [-\omega(t+1, T) \xi_{t+1}] \\
 &= \exp (r_t + \omega(t+1, T) \omega(t+1, S))
 \end{aligned}$$

and therefore $\lambda_t^{\mathbb{Q}^{(S)}}(\rho, 1) = \log E_t^{\mathbb{Q}^{(S)}} \{ \exp [\rho(t+1, T)] \} - r_t = \omega(t+1, T) \omega(t+1, S)$.

Exercise N° 10 [No-arbitrage restrictions for the short rate and spread].

We have a bivariate Gaussian VAR(1) ATSM given by:

$$\begin{aligned}
 x_{t+1} &= \nu + \Phi x_t + \Sigma \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, I_2) \quad (\text{under } \mathbb{P}) \\
 M_{t,t+1} &= \exp \left[-\beta - \alpha' x_t + \Gamma_t' \varepsilon_{t+1} - \frac{1}{2} \Gamma_t' \Gamma_t \right], \quad (\text{SDF}) \\
 \Gamma_t &= \Gamma(x_t) = (\gamma_o + \gamma x_t), \\
 R(t, h) &= -\frac{C_h'}{h} x_t - \frac{D_h}{h}, \\
 C_h &= -\alpha + (\Phi + \Sigma \gamma)' C_{h-1} = -\alpha + \Phi^{*'} C_{h-1}, \\
 D_h &= -\beta + C_{h-1}' (\nu + \Sigma \gamma_o) + \frac{1}{2} C_{h-1}' (\Sigma \Sigma') C_{h-1} + D_{h-1}, \\
 C_0 &= 0, D_0 = 0,
 \end{aligned}$$

where $x_t = (r_t, S_t)'$, with $r_t = R(t, t+1)$ the yield with the shortest maturity in our data base (it is the short rate) and $S_t = R_t - r_t$ the spread between the long rate (the yield with the longest maturity in our data base) and the short rate.

I have to impose no-arbitrage restrictions on both components of the factor (x_t) given that they contains yields at different maturities.

First, I have to impose that $R(t, t+1) = r_t$: this condition generates the no-arbitrage restriction $R(t, 1) = \beta + \alpha' x_t = \beta + \alpha_1 r_t + \alpha_2 S_t = r_t$. Clearly, $r_t = \beta + \alpha' x_t = \beta + \alpha_1 r_t + \alpha_2 S_t$ if and only if $\beta = 0$, $\alpha_1 = 1$ and $\alpha_2 = 0$. These conditions are equivalent to $C_1 = -(1, 0)$ and $D_1 = 0$.

Second, let us denote by H the longest maturity in our data base. I have to impose that $R(t, t+H) = R_t$ for any t . In this case we have:

$$\begin{aligned} -\frac{1}{H}[C_{1,H} r_t + C_{2,H} S_t + D_H] &= R_t \\ \Leftrightarrow C_{1,H} r_t + C_{2,H} (R_t - r_t) + D_H &= -H R_t \\ \Leftrightarrow [C_{1,H} - C_{2,H}] r_t + C_{2,H} R_t + D_H &= -H R_t \\ \Leftrightarrow C_{1,H} = C_{2,H}, \quad C_{2,H} = -H, \quad D_H = 0, \end{aligned}$$

that is $C_H = -H(1, 1)'$ and $D_H = 0$.