1 Derivation

HJB is

$$0 = \rho \theta V_t \left(\frac{C_t^{(1-\gamma)\theta}}{((1-\gamma)V_t)^{\frac{1}{\theta}}} - 1 \right) + \frac{E[dV_t]}{dt}$$

We know V_t is homogeneous in C_t

$$V_t = \frac{C_t^{1-\gamma}}{1-\gamma} G_t$$

Substituting in HJB, we obtain

$$0 = \frac{\rho \theta}{1 - \gamma} C_t^{1 - \gamma} G_t (G_t^{-\frac{1}{\theta}} - 1) + \frac{C_t^{1 - \gamma}}{1 - \gamma} E \frac{dG_t}{dt} + \frac{G_t}{1 - \gamma} E \frac{dC_t^{1 - \gamma}}{dt}$$

Using Ito,

$$E\left[\frac{dC_t^{1-\gamma}}{C_t^{1-\gamma}}\right] = \left[(1-\gamma)\mu_{Ct} - \frac{1}{2}(1-\gamma)\gamma\sigma_{Ct}^2\right]dt$$

We obtain

$$0 = \rho \theta (G_t^{1 - \frac{1}{\theta}} - G_t) + E \frac{dG_t}{dt} + G_t ((1 - \gamma)\mu_{Ct} - \frac{1}{2}(1 - \gamma)\gamma \sigma_{Ct}^2)$$

2 Long run risk model

The evolution of consumption is driven by two state variables μ_t and σ_t :

$$\frac{dC_t}{C_t} = \mu_t dt + \nu_D \sqrt{\sigma_t} dZ_t$$

$$d\mu_t = \kappa_\mu (\bar{\mu} - \mu_t) dt + \nu_\mu \sqrt{\sigma_t} dZ_t^\mu$$

$$d\sigma_t = \kappa_\sigma (1 - \sigma_t) dt + \nu_\sigma \sqrt{\sigma_t} dZ_t^\sigma$$

We write $G_t = G(\mu, \sigma)$ and we get the PDE

$$0 = \rho \theta [G^{1-\frac{1}{\theta}} - G] + G((1-\gamma)\mu - \frac{1}{2}(1-\gamma)\gamma\nu_D^2\sigma)$$
$$+ \kappa_\mu (\bar{\mu} - \mu)\frac{\partial G}{\partial \mu} + \kappa_\sigma (1-\sigma)\frac{\partial G}{\partial \sigma}$$
$$+ \frac{1}{2}\nu_\mu^2 \sigma \frac{\partial^2 G}{\partial \mu^2} + \frac{1}{2}\nu_\sigma^2 \sigma \frac{\partial^2 G}{\partial \sigma^2}$$

Boundary coundition = reflectiving barrier

$$\partial_{\mu}G(\underline{u},\sigma) = 0$$

$$\partial_{\mu}G(\overline{u},\sigma) = 0$$

$$\partial_{\sigma}G(u,\underline{\sigma}) = 0$$

$$\partial_{\sigma}G(u,\overline{\sigma}) = 0$$

We can solve this PDE through the following finite difference scheme:

$$0 = \rho \theta [(G_{ij}^{n+1})^{1-\frac{1}{\theta}} - G_{ij}^{n+1}] + G_{ij}^{n+1} ((1-\gamma)\mu_i - \frac{1}{2}(1-\gamma)\gamma\nu_D^2\sigma_j)$$

$$+ \kappa_{\mu_i}(\bar{\mu} - \mu_i)^+ (G_{i+1,j}^{n+1} - G_{i,j}^{n+1}) + \kappa_{\mu_i}(\bar{\mu} - \mu_i)^- (G_{i,j}^{n+1} - G_{i-1,j}^{n+1})$$

$$+ \kappa_{\sigma_j}(1-\sigma_j)^+ (G_{i,j+1}^{n+1} - G_{i,j}^{n+1}) + \kappa_{\sigma_j}(1-\sigma_j)^- (G_{i,j}^{n+1} - G_{i,j-1}^{n+1})$$

$$+ \frac{1}{2}\nu_{\mu_i}^2 \sigma_j (G_{i+1,j}^{n+1} - 2G_{i,j}^{n+1} + G_{i-1,j}^{n+1}) + \frac{1}{2}\nu_{\sigma_j}^2 \sigma_j (G_{i,j+1}^{n+1} - 2G_{i,j}^{n+1} + G_{i,j-1}^{n+1})$$

with usual ghost nodes to satisfy boundary conditions. The scheme satisfies the monotonicity condition of the Barles-Souganadis Theorem.

- monotonicity in $G_{i+1,j}{}_{i-1}^{n+1}, G_{i-1,j}{}_{i-1}^{n+1}, G_{i,j-1}{}_{i-1}^{n+1}, G_{i,j-1}{}_{i+1}^{n+1}$ by upwinding (similarly to Achdou et al., 2014)
- monoticity in $G_{i,j}^n$ because ... there is no term in $G_{i,j}^n$. We do need a fully explicit scheme : if $(G_{ij}^{n+1})^{1-\frac{1}{\theta}}$ was replaced by $(G_{ij}^n)^{1-\frac{1}{\theta}}$, the scheme would not be decreasing in G_{ij}^n for $\theta < 0$.

Contrary to the schemes of Achdou et al., 2014, the scheme contains a non linear term in G_{ij}^{n+1} . We can solve this non-linear scheme by Newton method (first order taylor approximation of the non linear term), i.e. by iterating

$$\begin{split} 0 &= \rho(G_{ij}^{n})^{1-\frac{1}{\theta}} + \rho(\theta-1)(G_{ij}^{n})^{-\frac{1}{\theta}}G_{ij}^{n+1} \\ &- \rho\theta G_{ij}^{n+1} + G_{ij}^{n+1}((1-\gamma)\mu_{i} - \frac{1}{2}(1-\gamma)\gamma\nu_{D}^{2}\sigma_{j}) \\ &+ \kappa_{\mu_{i}}(\bar{\mu} - \mu_{i})^{+}(G_{i+1,j}^{n+1} - G_{i,j}^{n+1}) + \kappa_{\mu_{i}}(\bar{\mu} - \mu_{i})^{-}(G_{i,j}^{n+1} - G_{i-1,j}^{n+1}) \\ &+ \kappa_{\sigma_{j}}(1-\sigma_{j})^{+}(G_{i,j+1}^{n+1} - G_{i,j}^{n+1}) + \kappa_{\sigma_{j}}(1-\sigma_{j})^{-}(G_{i,j}^{n+1} - G_{i,j-1}^{n+1}) \\ &+ \frac{1}{2}\nu_{\mu_{i}}^{2}\sigma_{j}(G_{i+1,j}^{n+1} - 2G_{i,j}^{n+1} + G_{i-1,j}^{n+1}) + \frac{1}{2}\nu_{\sigma_{j}}^{2}\sigma_{j}(G_{i,j+1}^{n+1} - 2G_{i,j}^{n+1} + G_{i,j-1}^{n+1}) \end{split}$$

This defines a linear semi explicit scheme ¹. Note that this scheme does not satisfy the monotonicity condition of the Barles-Souganadis Theorem: the derivative of the scheme wrt G_{ij}^n is

$$\rho(1-\theta)(G_{ij}^n)^{-\frac{1}{\theta}}(1-\frac{G_{ij}^{n+1}}{G_{ij}^n})$$

Yet, this scheme converges because (i) the non linear scheme satisfies Barles-Souganadis Theorem (ii) Newton method converges to the non linear scheme

We can also solve this non linear scheme by any off the shelf non linear solver. The NLsolve package in Julia uses the Powell Dog-leg method. In this case, the updating step is a mix of gradient and Newton steps.

Actually, the schemes used in Achdou et al., 2014 can be obtained in this way.

3 Comparaison

Name	BY04	BY04	This paper	This paper	Link
mean growth rate	μ	0.0015	$ar{\mu}$	0.0015	$\mu = \bar{\mu}$
mean volatility	σ^2	0.00006084	$ u_D$	0.0078	$\sqrt{\sigma^2} = \nu_D$
growth persistence	ρ	0.979	κ_{μ}	0.0212	$-\log(\rho) = \kappa_{\mu}$
volatility persistence	ν_1	0.987	κ_{σ}	0.0131	$-\log\left(\nu_1\right) = \kappa_{\sigma}$
growth rate volatility	$arphi_e$	0.044	$ u_{\mu}$	0.0003432	$\varphi_e \times \sqrt{\sigma^2} = \nu_\mu$
volatility volatility	σ_w	0.0000023	ν_{σ}	0.0378	$\sigma_w/\sigma^2 = \nu_\sigma$
time discount	δ	0.998	ρ	0.002	$-\log\left(\delta\right) = \rho$
RRA	$1 - \gamma(RRA)$	7.5 or 10	$1-\gamma$	-6.5 or -9	$1 - RRA = 1 - \gamma$
IES	ψ	1.5	ψ	1.5	$\psi = \psi$

Also, $\theta = (1 - \gamma)/(1 - 1/\psi) = -19.50$ or -27. Let's express the consumption to wealth ratio k_t in term of state variables.

$$V = G_t k_t^{1-\gamma} \frac{W^{1-\gamma}}{(1-\gamma)}$$

FOC for consumption can be written

$$\frac{C_t}{W_t} = \rho^{\psi} k_t^{1-\psi} G_t^{\frac{1-\psi}{1-\gamma}}$$

General equilibrium gives

$$k_t = \rho G_t^{-1/\theta}$$

Bansal Yaron find

$$\begin{split} \frac{1}{\theta} \log G_t - \log \rho &\approx A_1 \mu_t + A_2 \nu_D^2 \sigma_t \\ A1 &= \frac{1 - \frac{1}{\psi}}{1 - 0.997 e^{-\kappa_\mu}} \\ A2 &= 0.5 \theta \frac{(1 - \frac{1}{\psi})^2 + (A_1 \kappa_1 \frac{\nu_\mu}{\nu_D^2})^2}{1 - 0.997 e^{-\kappa_\sigma}} \end{split}$$