

# An FEM Analysis of Risk-Sensitive Real Business Cycles

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## Abstract

In this project, we will try to apply Finite Element Method to the model used in [Tallarini \(2000\)](#).

## 1 Model

The model is the usual business cycle model except for consumers preferences. Consumer's preferences are given by a subclass of preferences defined in [Epstein and Zin \(1989\)](#). The inter-temporal elasticity of substitution is 1 while the coefficient for relative risk-aversion can be varied freely. Hence the non-expected utility of an agent at date  $t$  is defined recursively as follows:

$$U_t = \log c_t + \beta \frac{1}{(1 - \beta)(1 - \chi)} \log(E_t[\exp\{(1 - \beta)(1 - \chi)U_{t+1}\}]) \quad (1)$$

Furthermore, if  $\sigma = 2(1 - \beta)(1 - \chi)$ , then:

$$U_t = \log c_t + \beta(2/\sigma) \log(E_t[\exp\{(\sigma/2)U_{t+1}\}])$$

Allowing for elastic labor supply, preferences will be in the following form:

$$U_t = \log C_t + \theta \log L_t + \beta(2/\sigma) \log(E_t[\exp\{(\sigma/2)U_{t+1}\}]) \quad (2)$$

where  $L_t$  is leisure. [Tallarini \(2000\)](#) uses a random walk with drift for the stochastic process governing productivity. He then divides everything by productivity to make problem stationary. While this is a valid approach, we will use the usual approach of having a constant productivity growth and using a stationary process for TFP.<sup>1</sup> Therefore, the production

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<sup>1</sup>Random walk is not a stationary process and therefore we cannot discretize the state space of shocks. So we will assume, instead, a mean-reverting process for TFP in order to apply methods described in [Tauchen \(1986\)](#).

side of the economy is given by

$$\begin{aligned} Y_t &= K_t^\alpha (N_t(1+g)^t X_t)^{1-\alpha} \\ \log X_{t+1} &= \rho \log X_t + \epsilon_{t+1} \\ K_{t+1} &= (1-\delta)K_t + Y_t - C_t \end{aligned}$$

We define small letters to be variable divided by growth rate of TFP:  $v_t = V_t/(1+g)^t$ . Then, the Pareto problem becomes the following:

$$\begin{aligned} \max_{C_t, L_t, K_t, Y_t, U_t} \quad & U_0 \\ \text{s.t.} \quad & C_t + K_{t+1} = (1-\delta)K_t + Y_t \\ & Y_t = K_t^\alpha (N_t(1+g)^t X_t)^{1-\alpha} \\ & U_t = \log C_t + \theta \log(1 - N_t) + \beta(2/\sigma) \log(E_t[\exp\{(\sigma/2)U_{t+1}\}]) \end{aligned}$$

We define  $u_t = U_t - t \frac{\log(1+g)}{1-\beta} - \frac{\beta}{(1-\beta)^2} \log(1+g)$ . Then one can show that  $u_t$  satisfies the following equation:

$$u_t = \log c_t + \theta \log(1 - n_t) + \beta(2/\sigma) \log(E_t[\exp\{(\sigma/2)u_{t+1}\}])$$

Therefore the Pareto problem is equivalent to the following problem:

$$\begin{aligned} \max_{c_t, n_t, k_t, y_t, u_t} \quad & u_0 \\ \text{s.t.} \quad & c_t + (1+g)k_{t+1} = (1-\delta)k_t + k_t^\alpha (n_t x_t)^{1-\alpha} \quad (3) \\ & u_t = \log c_t + \theta \log(1 - n_t) + \beta(2/\sigma) \log(E_t[\exp\{(\sigma/2)u_{t+1}\}]) \quad (4) \\ & \log x_{t+1} = \rho \log x_t + \epsilon_{t+1} \end{aligned}$$

The FOCs for this problem are the following:

$$\frac{\theta}{1 - n_t} = \frac{1}{c_t} (1 - \alpha) k_t^\alpha (n_t x_t)^{-\alpha} x_t \quad (5)$$

$$1 = \frac{\beta}{1+g} E_t \left[ \frac{c_t}{c_{t+1}} \frac{\exp((\sigma/2)u_{t+1})}{E_t[\exp((\sigma/2)u_{t+1})]} \{1 - \delta + \alpha k_{t+1}^{\alpha-1} (n_{t+1} x_{t+1})^{1-\alpha}\} \right] \quad (6)$$

Therefore the policy functions that we have to solve for are  $k'(k, x)$ ,  $c(k, x)$ ,  $n(k, x)$ ,  $u(k, x)$  using equations (3), (4), (5) and (6).

The function to be solved for in [McGrattan \(1996\)](#) is  $c(k, s)$ . Here we will look for the following function:

$$\begin{pmatrix} c(k, x) \\ u(k, x) \end{pmatrix} = \sum_{j=1}^m \alpha_j^x \Phi_j(k) = \sum_{j=1}^m \begin{pmatrix} \alpha_{j,c}^x \\ \alpha_{j,u}^x \end{pmatrix} \Phi_j(k) \quad (7)$$

where  $\Phi_j(k)$  is a one-dimensional basis function and  $\alpha_j^x \in \mathbb{R}^2$ .

The residual function,  $R(k, x)$ , in this case, would be

$$R(k, x; \alpha) = \begin{pmatrix} \log c(k, x) + \theta \log(1 - n(k, x)) + \beta(2/\sigma) \log(E_t\{\exp((\sigma/2)u(\tilde{k}, x'))\}) - u(k, x) \\ \frac{\beta}{1+g} E_t \left[ \frac{c(k, x)}{c(\tilde{k}, x')} \frac{\exp((\sigma/2)u(\tilde{k}, x'))}{E_t[\exp((\sigma/2)u(\tilde{k}, x'))]} (1 - \delta + \alpha k_{t+1}^{\alpha-1} (n_{t+1} x_{t+1})^{1-\alpha}) \right] - 1 \end{pmatrix} \quad (8)$$

where  $n(k, x)$  is the solution to the following equation:

$$(1 - \alpha)(1 - n)(nx)^{-\alpha} x k^\alpha - \theta c(k, x) = 0$$

and  $k' = \frac{1}{1+g} ((nx)^{1-\alpha} k^\alpha + (1 - \delta)k - c(k, x))$ .

In order to differentiate (8), we define it as a function of  $z = (c, c', k', n, n', u, u')$ . We can calculate the derivative of  $R$  w.r.t  $z$ . Then, we can calculate  $dz/du, dz/dc$  and using the chain rule, we can calculate  $R_\alpha$ . We have:

$$R_1 = \log c + \theta \log(1 - n) + \beta(2/\sigma) \log\left(\sum_{x'} \pi_{x',x} \exp((2/\sigma)u'(x'))\right) - u \quad (9)$$

Therefore,

$$\begin{aligned} R_{1c} &= \frac{1}{c} \\ R_{1n} &= -\frac{\theta}{1 - n} \\ R_{1u} &= -1 \\ R_{1u'(x')} &= \beta \frac{\pi_{x',x} \exp((2/\sigma)u'(x'))}{\sum_{x'} \pi_{x',x} \exp((2/\sigma)u'(x'))} \end{aligned}$$

Moreover,

$$\begin{aligned} R_2 &= \frac{\beta}{1 + g} \sum_{x'} \pi_{x',x} \frac{c}{c'(x')} \frac{\exp((\sigma/2)u'(x'))}{\sum_{x'} \pi_{x',x} \exp((\sigma/2)u'(x'))} (1 - \delta + \alpha k'^{\alpha-1} (n'(x')x')^{1-\alpha}) - 1 \\ &= \frac{\beta}{1 + g} \frac{\sum_{x'} \pi_{x',x} \frac{c}{c'(x')} \exp((\sigma/2)u'(x')) [1 - \delta + \alpha k'^{\alpha-1} (n'(x')x')^{1-\alpha}]}{\sum_{x'} \pi_{x',x} \exp((\sigma/2)u'(x'))} - 1 \end{aligned} \quad (10)$$

For less numerical complexity, we redefine  $R_2$  to be the following

$$R_2 = \frac{\beta}{1 + g} \sum_{x'} \pi_{x',x} \frac{c}{c'(x')} \exp((\sigma/2)u'(x')) [1 - \delta + \alpha k'^{\alpha-1} (n'(x')x')^{1-\alpha}] - \sum_{x'} \pi_{x',x} \exp((\sigma/2)u'(x')) \quad (11)$$

Hence, the derivatives are

$$\begin{aligned} R_{2c} &= \frac{R_2 + \sum_{x'} \pi_{x',x} \exp((\sigma/2)u'(x'))}{c} \\ R_{2c'(x')} &= -\frac{\beta}{1 + g} \pi_{x',x} \frac{c}{c'(x')^2} \exp((\sigma/2)u'(x')) [1 - \delta + \alpha k'^{\alpha-1} (n'(x')x')^{1-\alpha}] \\ R_{2k'} &= \frac{\beta}{1 + g} \sum_{x'} \pi_{x',x} \frac{c}{c'(x')} \exp((\sigma/2)u'(x')) [\alpha(\alpha - 1) k'^{\alpha-2} (n'(x')x')^{1-\alpha}] \\ R_{2n'(x')} &= \frac{\beta}{1 + g} \pi_{x',x} \frac{c}{c'(x')} \exp((\sigma/2)u'(x')) [\alpha(1 - \alpha) k'^{\alpha-1} (n'(x')x')^{-\alpha} x'] \\ R_{2u'(x')} &= \frac{\sigma\beta}{2(1 + g)} \pi_{x',x} \frac{c}{c'(x')} \exp((\sigma/2)u'(x')) [1 - \delta + \alpha k'^{\alpha-1} (n'(x')x')^{1-\alpha}] \\ &\quad - \frac{\sigma}{2} \pi_{x',x} \exp((\sigma/2)u'(x')) \end{aligned}$$

We also have:

$$\begin{aligned}
[-\alpha n^{-\alpha-1} - (1-\alpha)n^{-\alpha}] \frac{\partial n}{\partial c} &= \frac{\theta}{(1-\alpha)k^\alpha x^{1-\alpha}} \Rightarrow \frac{\partial n}{\partial c} = \frac{\theta n^\alpha}{(1-\alpha)k^\alpha x^{1-\alpha}(-(1-\alpha) - \alpha n^{-1})} \\
\frac{\partial k'}{\partial c} &= \frac{(1-\alpha)k^\alpha (nx)^{-\alpha} x}{1+g} \frac{\partial n}{\partial c} - \frac{1}{1+g} \\
\frac{\partial n'(x')}{c'(x')} &= \frac{\theta n'(x')^\alpha}{(1-\alpha)k'^\alpha x'^{1-\alpha}(-(1-\alpha) - \alpha n'(x')^{-1})} \\
\frac{\partial n'(x')}{k'} &= -\frac{\alpha \theta n'(x')^\alpha c'(x')}{(1-\alpha)k'^{\alpha-1} x'^{1-\alpha}(-(1-\alpha) - \alpha n'(x')^{-1})}
\end{aligned}$$

Therefore, taking derivative with respect to  $\alpha_{j,c}^{\bar{x}}$ , we have:

Contemporary derivatives

$$\frac{\partial c(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = \Phi_j(k) \mathbf{1}[\bar{x} = x] \quad (12)$$

$$\frac{\partial n(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = \frac{\partial n}{\partial c} \Phi_j(k) \mathbf{1}[\bar{x} = x] \quad (13)$$

$$\frac{\partial u(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = 0 \quad (14)$$

Future Derivatives

$$\frac{\partial k'(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = \frac{\partial k'}{\partial c} \Phi_j(k) \mathbf{1}[\bar{x} = x] \quad (15)$$

$$\begin{aligned}
\frac{\partial c'(x')}{\partial \alpha_{j,c}^{\bar{x}}} &= \frac{\partial c(k'(k, x; \alpha), x'; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = \frac{\partial c}{\partial k} \Big|_{k'(k, x; \alpha)} \frac{\partial k'}{\partial c} \Phi_j(k) \mathbf{1}[\bar{x} = x] + \mathbf{1}[\bar{x} = x'] \Phi_j(k') \\
&= \left( \sum_{i=1}^m \alpha_{i,c}^{x'} \Phi_i'(k') \right) \frac{\partial k'}{\partial c} \Phi_j(k) \mathbf{1}[\bar{x} = x] + \mathbf{1}[\bar{x} = x'] \Phi_j(k')
\end{aligned} \quad (16)$$

$$\frac{\partial n'(k', x'; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = \frac{\partial n'(x')}{\partial c'(x')} \frac{\partial c'(x')}{\partial \alpha_{j,c}^{\bar{x}}} + \frac{\partial n'(x')}{\partial k'} \frac{\partial k'}{\partial c} \Phi_j(k) \mathbf{1}[\bar{x} = x] \quad (17)$$

$$\frac{\partial u'(x')}{\partial \alpha_{j,c}^{\bar{x}}} = \frac{\partial u(k', x'; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = \left( \sum_{i=1}^m \alpha_{i,u}^{x'} \Phi_i'(k') \right) \frac{\partial k'}{\partial c} \Phi_j(k) \mathbf{1}[\bar{x} = x] \quad (18)$$

Applying chain rule:

$$\frac{\partial R_1(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = R_{1c} \frac{\partial c(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} + R_{1n} \frac{\partial n(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} + R_{1u} \times 0 \quad (19)$$

$$+ \sum_{x'} R_{1u'(x')} \frac{\partial u'(k', x'; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} \quad (20)$$

$$\frac{\partial R_2(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} = R_{2c} \frac{\partial c(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} + R_{2k'} \frac{\partial k'(k, x; \alpha)}{\partial \alpha_{j,c}^{\bar{x}}} \quad (21)$$

$$+ \sum_{x'} \left\{ R_{2c'(x')} \frac{\partial c'(x')}{\partial \alpha_{j,c}^{\bar{x}}} + R_{2n'(x')} \frac{\partial n'(x')}{\partial \alpha_{j,c}^{\bar{x}}} + R_{2u'(x')} \frac{\partial u'(x')}{\partial \alpha_{j,c}^{\bar{x}}} \right\} \quad (22)$$

For derivative w.r.t.  $\alpha_{j,u}^{\bar{x}}$ , we have the following:

Contemporary derivatives

$$\frac{\partial c(k, x; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = 0 \quad (23)$$

$$\frac{\partial n(k, x; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = 0 \quad (24)$$

$$\frac{\partial u(k, x; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = \mathbf{1}[\bar{x} = x] \Phi_j(k) \quad (25)$$

Future Derivatives

$$\frac{\partial k'(k, x; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = 0 \quad (26)$$

$$\frac{\partial c'(x')}{\partial \alpha_{j,u}^{\bar{x}}} = \frac{\partial c(k'(k, x; \alpha), x'; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = 0 \quad (27)$$

$$\frac{\partial n'(k', x'; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = 0 \quad (28)$$

$$\frac{\partial u'(x')}{\partial \alpha_{j,u}^{\bar{x}}} = \mathbf{1}[\bar{x} = x'] \Phi_j(k') \quad (29)$$

and hence,

$$\frac{\partial R_1(k, x; \alpha)}{\partial \alpha_{j,u}^{\bar{x}}} = -\Phi_j(k) \mathbf{1}[\bar{x} = x] + R_{1u'(\bar{x})} \Phi_j(k') \quad (30)$$

$$\frac{\partial R_2(k, x; \alpha)}{\partial \alpha_{j,u}^x} = R_{2u'(\bar{x})} \Phi_j(k') \quad (31)$$

### 1.1 Calculating Utility When $\sigma = 0$

In this section, I describe how to calculate utility in a one-sector growth model with expected utility, i.e.  $\sigma = 0$ , and when we know the consumption function,  $c(k, s)$ . Suppose that our grid points for  $k$  are  $\{k_j\}_{j=1}^{n_x}$  and  $\{s_i\}_{i=1}^{n_s}$  for the stochastic state  $s$ . A consumption function is comprised of  $n_x \times n_s$  numbers,  $c(k_j, s_i)$ . What we are looking for is  $n_x \times n_s$  numbers  $u(k_j, s_i)$  given the fact that utility  $u(k, s)$  is a linear combination of basis function over our grid. Since we know  $c(k_j, s_i)$ , we can calculate  $n(k_j, s_i)$  using the Intra-temporal Euler Equation. Having found hours, we can calculate next period's capital  $k'(k_j, s_i)$ . Therefore, we have the following relation for all  $i, j$ :

$$u(k_j, s_i) = \log(c(k_j, s_i)) + \theta \log(1 - n(k_j, s_i)) + \beta \sum_{s'} \pi_{s,s'} u(k'(k_j, s_i), s') \quad (32)$$

Suppose, we find that  $k'(k_j, s_i) \in [k_{l(j,i)}, k_{l(j,i)+1}]$ , then substituting in (32), we will have:

$$\begin{aligned} u(k_j, s_i) &= \log(c(k_j, s_i)) + \theta \log(1 - n(k_j, s_i)) \\ &+ \beta \sum_{s'} \pi_{s,s'} \left\{ \frac{k_{l(j,i)+1} - k'(k_j, s_i)}{k_{l(j,i)+1} - k_{l(j,i)}} u(k_{l(j,i)}, s') + \frac{k'(k_j, s_i) - k_{l(j,i)}}{k_{l(j,i)+1} - k_{l(j,i)}} u(k_{l(j,i)+1}, s') \right\} \end{aligned} \quad (33)$$

Now, define  $\mathbf{u}$  to be the vector of  $\{u(k_j, s_i)\}_{j,i}$  and define  $\mathcal{P}_{ij}$  to be the vector operation equivalent of second line in (33). Then, equation (33) is equivalent to the following equation:

$$(I - \beta \mathcal{P}) \mathbf{u} = \log(\mathbf{c}) + \theta \log(1 - \mathbf{n}) \quad (34)$$

This method closely follows, [Ljungqvist and Sargent \(2004\)](#) section 4.5. Notice that we cannot do this when  $\sigma \neq 0$  since equation (32) becomes nonlinear and we have to use finite element method to estimate  $\mathbf{u}$ .

## 2 Computer Code

### 2.1 List of Variables

Capital :	$\mathbf{k} : k_t;$	$\mathbf{kp} : k_{t+1};$	$\mathbf{grid} : \mathbf{ka}$
Consumption :	$\mathbf{c} : c_t;$	$\mathbf{cp} : c_{t+1}$	
Hours :	$\mathbf{hr} : n_t;$	$\mathbf{hrp} : n_{t+1}$	
Utility :	$\mathbf{u} : u_t;$	$\mathbf{up} : u_{t+1}$	
Basis :	$\mathbf{basis1}, \mathbf{basis2} : \Phi_j(k);$	$\mathbf{basis1p}, \mathbf{basis2p} : \Phi_j(k')$	
Basis Derivative :	$\mathbf{dbasis1}, \mathbf{dbasis2} : \Phi'_j(k);$	$\mathbf{dbasis1p}, \mathbf{dbasis2p} : \Phi'_j(k')$	
Derivatives :	$\mathbf{dndc} : \frac{\partial n}{\partial c};$	$\mathbf{dkpdc} : \frac{\partial k'}{\partial c};$	$\mathbf{dnpcp} : \frac{\partial n'(x')}{\partial c'(x')}$
	$\mathbf{dnpcp} : \frac{\partial n'(x')}{\partial k'}$		

## References

- EPSTEIN, L. G. AND S. E. ZIN (1989): “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework,” *Econometrica*, 57, 937–969.
- LJUNGQVIST, L. AND T. J. SARGENT (2004): *Recursive Macroeconomic Theory*, MIT Press.
- MCGRATTAN, E. R. (1996): “Solving the stochastic growth model with a finite element method,” *Journal of Economic Dynamics and Control*, 20, 19–42.
- TALLARINI, T. D. (2000): “Risk-Sensitive Real Business Cycles,” *Journal of Monetary Economics*, 45, 507–532.
- TAUCHEN, G. (1986): “Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions,” *Economics Letters*, 20, 177–81.