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1. a. Given $P = \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix}$, the economic interpretation of α & β are as follows,

i. $\underline{\alpha = P_{11}}$ is the probability an individual who is unemployed in a given quarter remains unemployed in the next quarter

ii. $\underline{\beta = P_{22}}$ is the probability an individual who is employed in a given quarter remains employed in the next quarter

b. The rows of P sum to one since they constitute a probability measure (note that this also requires $\alpha, \beta \in [0, 1]$, but this is not given). In other words, since there are two states in the state space, if time is discrete, the probabilities of transitioning to either state must sum to one.

c. If $\alpha = 1$, then state U (unemployed) is an absorbing state. Likewise, if $\beta = 1$, then state E (employed) is an absorbing state. However, this model does not necessarily have an absorbing state.

d. Note,

$$P^2 = \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix} \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix} = \begin{bmatrix} \alpha^2 + (1-\alpha)(1-\beta) & \alpha(1-\alpha) + (1-\alpha)\beta \\ (1-\beta)\alpha + \beta(1-\beta) & (1-\beta)(1-\alpha) + \beta^2 \end{bmatrix}.$$

Then, $\underline{P(U_{t+2} | E_t)} = [P^2]_{EU} = (1-\beta)\alpha + \beta(1-\beta)$.

c. We can express the marginal probability of being in state y^L at time $t+1$ as,

$\gamma_{t+1}(y^L) = \mathbb{P}(y_{t+1} = y^L)$. Since the state space Y is mutually exclusive & exhaustive, the Law of Total Probability gives,

$$= \sum_s \mathbb{P}(y_{t+1} = y^L | y_t = s), s \in Y = \{y^U, y^E\}. \text{ Since } \{y_i\} \text{ follows a Markov chain,}$$

$$= \sum_s \mathbb{P}(y_{t+1} = y^L | y_t = s) \mathbb{P}(y_t = s).$$

i. If $y^L = y^U$, we have,

$$\gamma_{t+1}(y^U) = \mathbb{P}(y_{t+1} = y^U | y_t = y^U) \mathbb{P}(y_t = y^U) + \mathbb{P}(y_{t+1} = y^U | y_t = y^E) \mathbb{P}(y_t = y^E).$$

Using the transition matrix P , we can express this as,

$$\underline{\gamma_{t+1}(y^U)} = \alpha \mathbb{P}(y_t = y^U) + (1-\beta) \mathbb{P}(y_t = y^E) = \underline{\alpha \gamma_t(y^U) + (1-\beta) \gamma_t(y^E)}$$

ii. If $y^L = y^E$, we similarly get,

$$\underline{\gamma_{t+1}(y^E)} = (1-\alpha) \gamma_t(y^U) + \beta \gamma_t(y^E)$$

$$f. \text{ Observe, } \gamma_{t+1}(y^U) = [\gamma_t(y^U) \quad \gamma_t(y^E)] \begin{bmatrix} \alpha \\ 1-\beta \end{bmatrix} \stackrel{?}{=} \gamma_t(y^U) \quad \gamma_t(y^E)$$

$$\gamma_{t+1}(y^E) = [\gamma_t(y^U) \quad \gamma_t(y^E)] \begin{bmatrix} 1-\alpha \\ \beta \end{bmatrix}.$$

$$\text{Then, } [\gamma_{t+1}(y^U) \quad \gamma_{t+1}(y^E)] = [\gamma_t(y^U) \quad \gamma_t(y^E)] \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix}$$

$$\Leftrightarrow \gamma_{t+1} = \gamma_t P. \square$$

g. We proceed with a proof by induction. Let $\{X_i\}_{i=1}^{t+1}$ be a random vector corresponding to the state of the stochastic process at time i .

base step: We are given $X_0 \sim \psi_0$. From part f, the marginal distribution of X_1 is given by, $\psi_1 = \psi_0 P$. As such, $X_1 \sim \psi_0 P$.

inductive step: Suppose the given property holds $\forall i \in \{1, \dots, t-1\}$. As such, $X_{t-1} \sim \psi_0 P^{t-1} \Leftrightarrow \psi_{t-1} = \psi_0 P^{t-1}$. From part f, $\psi_t = \psi_{t-1} P$. By the inductive assumption,

$$= [\psi_0 P^{t-1}] P$$

$$\Leftrightarrow \psi_t = \psi_0 P^t \Rightarrow X_t \sim \psi_0 P^t.$$

Taken collectively, the base case & inductive step gives,
 $X_0 \sim \psi_0 \Rightarrow X_t \sim \psi_0 P^t$. \square

h. Let time t denote the initial quarter where the individual is employed. WLOG, since $\{y_i\}$ follows a Markov process, let $t=0$. By part g., we can express the marginal distribution of y_i at time $t+n=n$ as,

$\psi_n = \psi_0 P^n$, where we are given $\psi_0 = (0 \ 1)$. Evaluating,

$$= [0 \ 1] \begin{bmatrix} p_{11}^n & p_{12}^n \\ p_{21}^n & p_{22}^n \end{bmatrix} = [0 \cdot p_{11}^n + 1 \cdot p_{21}^n \ 0 \cdot p_{12}^n + 1 \cdot p_{22}^n]$$

$= [p_{21}^n \ p_{22}^n]$. Thus, the probability of being unemployed n quarters after being employed is $\psi_n(y_u) = p_{21}^n$.

To find a closed form expression for p_{21}^n , we diagonalize P s.t. $P = Q \Lambda Q^{-1}$ where Q := eigenvector matrix & Λ := diagonal matrix of eigenvalues.

The eigenvalues for P satisfy,

$$\det(P - \lambda I) = 0 \Leftrightarrow \det \begin{bmatrix} \alpha - \lambda & 1 - \alpha \\ 1 - \beta & \beta - \lambda \end{bmatrix} = 0$$

$$\Leftrightarrow (\alpha - \lambda)(\beta - \lambda) - (1 - \alpha)(1 - \beta) = 0$$

$$\Leftrightarrow \alpha\beta - \lambda\alpha - \lambda\beta + \lambda^2 - [1 - \beta - \alpha + \alpha\beta] = 0$$

$$\Leftrightarrow \alpha\beta - \lambda\alpha - \lambda\beta + \lambda^2 - 1 + \beta + \alpha - \alpha\beta = 0$$

$$\Leftrightarrow \lambda^2 - \lambda\alpha - \lambda\beta + \beta + \alpha - 1 = 0$$

$$\Leftrightarrow \lambda^2 - (\alpha + \beta)\lambda + (\beta + \alpha - 1) = 0. \text{ Then,}$$

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

$$= \frac{\alpha + \beta \pm \sqrt{(\alpha^2 - 2\alpha + 1) + 2\alpha\beta + \beta^2 - 4\beta - 2\alpha + 3}}{2} = \frac{\alpha + \beta \pm \sqrt{(\alpha^2 - 2\alpha + 1) + (\beta^2 - 2\beta + 1) + 2(\alpha - 1)(\beta - 1)}}{2}$$

$$= \frac{\alpha + \beta \pm \sqrt{(\alpha + \beta - 2)^2}}{2}. \text{ Then, } \underline{\lambda}_1 = \frac{\alpha + \beta - \alpha - \beta + 2}{2} = \frac{2}{2} = 1$$

$$\underline{\lambda}_2 = \frac{\alpha + \beta + \alpha + \beta - 2}{2} = \frac{2[\alpha + \beta - 1]}{2} = \underline{\alpha + \beta - 1}$$

λ_1 & λ_2 are distinct if $\alpha \neq 1$ or $\beta \neq 1$; thus P will be diagonalizable.

The eigenvectors associated with each of λ_1 & λ_2 are,

$$\underline{\lambda_1 = 1}: (\rho - \lambda_1 I) \vec{v}_1 = \vec{0} \Leftrightarrow \left\{ \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix} - \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right\} \begin{bmatrix} v_1^{(1)} \\ v_1^{(2)} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} \alpha-1 & 1-\alpha \\ 1-\beta & \beta-1 \end{bmatrix} \begin{bmatrix} v_1^{(1)} \\ v_1^{(2)} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \Leftrightarrow (\alpha-1)v_1^{(1)} + (1-\alpha)v_1^{(2)} = 0 \\ (1-\beta)v_1^{(1)} + (\beta-1)v_1^{(2)} = 0$$

$$\Leftrightarrow v_1^{(1)} = v_1^{(2)} \text{ for } \alpha \neq 1, \beta \neq 1. \text{ Let } \vec{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

$$\underline{\lambda_2 = \alpha + \beta - 1}: (\rho - \lambda_2 I) \vec{v}_2 = \vec{0} \Leftrightarrow \begin{bmatrix} \alpha - \alpha - \beta + 1 & 1-\alpha \\ 1-\beta & \beta - \alpha - \beta + 1 \end{bmatrix} \begin{bmatrix} v_2^{(1)} \\ v_2^{(2)} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} 1-\beta & 1-\alpha \\ 1-\beta & 1-\alpha \end{bmatrix} \begin{bmatrix} v_2^{(1)} \\ v_2^{(2)} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Leftrightarrow (1-\beta)v_2^{(1)} + (1-\alpha)v_2^{(2)} = 0 \\ (1-\beta)v_2^{(1)} + (1-\alpha)v_2^{(2)} = 0$$

$$\Leftrightarrow v_2^{(2)} = -\frac{1-\beta}{1-\alpha} v_2^{(1)}, \alpha \neq 1 \Rightarrow (1-\beta)v_2^{(1)} + (1-\alpha)\left[-\frac{1-\beta}{1-\alpha} v_2^{(1)}\right] = 0$$

$$\Leftrightarrow (1-\beta)v_2^{(1)} = (1-\beta)v_1^{(1)} \Rightarrow \text{choose } v_2^{(1)} = 1-\alpha \Rightarrow v_2^{(2)} = \beta-1.$$

$$\text{Then, } \vec{v}_2 = \begin{bmatrix} 1-\alpha \\ \beta-1 \end{bmatrix}.$$

$$\text{Thus, } Q = [\vec{v}_1 \ \vec{v}_2] = \begin{bmatrix} 1 & 1-\alpha \\ 1 & \beta-1 \end{bmatrix}. \text{ The inverse is}$$

$$Q^{-1} = \frac{1}{\beta+\alpha-2} \begin{bmatrix} \beta-1 & \alpha-1 \\ -1 & 1 \end{bmatrix}. \text{ We proceed with finding } P_{21}^n$$

$$P^n = Q \Lambda^n Q^{-1} = \begin{bmatrix} 1 & 1-\alpha \\ 1 & \beta-1 \end{bmatrix} \begin{bmatrix} 1^n & 0 \\ 0 & (\alpha+\beta-1)^n \end{bmatrix} Q^{-1}$$

$$= \begin{bmatrix} 1 \cdot 1^n + (1-\alpha)(0) & 1 \cdot 0 + (1-\alpha)(\alpha+\beta-1)^n \\ 1 \cdot 1^n + (\beta-1)(0) & 1 \cdot 0 + (\beta-1)(\alpha+\beta-1)^n \end{bmatrix} Q^{-1}$$

$$= \frac{1}{\alpha+\beta-2} \begin{bmatrix} 1 & (1-\alpha)(\alpha+\beta-1)^n \\ 1 & (\beta-1)(\alpha+\beta-1)^n \end{bmatrix} \begin{bmatrix} \beta-1 & \alpha-1 \\ -1 & 1 \end{bmatrix}$$

$$\Rightarrow P_{21}^n = \frac{(\beta-1) - (\beta-1)(\alpha+\beta-1)^n}{\alpha+\beta-2} = \frac{(\beta-1)[1 - (\alpha+\beta-1)^n]}{\alpha+\beta-2}$$

As such, the probability of being unemployed n quarters after being employed is, $\gamma_n(y^U) = P_{21}^n = \frac{(\beta-1)[1-(\alpha+\beta-1)^n]}{\alpha+\beta-2}$.

$$\text{i. As } n \rightarrow \infty, \lim_{n \rightarrow \infty} P^n = \begin{bmatrix} 1 & 1-\alpha \\ 1 & \beta-1 \end{bmatrix} \begin{bmatrix} (1)^n & 0 \\ 0 & (\alpha+\beta-1)^n \end{bmatrix} Q^{-1}.$$

Under the assumption α or $\beta < 1$,

$$\lim_{n \rightarrow \infty} P^n = \begin{bmatrix} 1 & 1-\alpha \\ 1 & \beta-1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} Q^{-1}$$

$$= \frac{1}{\alpha+\beta-2} \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \beta-1 & \alpha-1 \\ -1 & 1 \end{bmatrix}$$

$$(\Leftarrow) \lim_{n \rightarrow \infty} P^n = \frac{1}{\alpha+\beta-2} \begin{bmatrix} \beta-1 & \alpha-1 \\ \beta-1 & \alpha-1 \end{bmatrix}. \text{ Thus,}$$

$\gamma^* = \left[\frac{\beta-1}{\alpha+\beta-2} \quad \frac{\alpha-1}{\alpha+\beta-2} \right]$ gives the stationary distribution

of the Markov chain. To verify,

$$\begin{aligned} \gamma^* P &= \left[\frac{\beta-1}{\alpha+\beta-2} \quad \frac{\alpha-1}{\alpha+\beta-2} \right] \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix} \\ &= \left[\frac{\alpha(\beta-1) + (\alpha-1)(1-\beta)}{\alpha+\beta-2} \quad \frac{(\beta-1)(1-\alpha) + (\alpha-1)\beta}{\alpha+\beta-2} \right] \\ &= \left[\frac{\cancel{\alpha\beta} - \cancel{\alpha\beta} + \alpha - \alpha\beta - 1 + \beta}{\alpha+\beta-2} \quad \frac{\cancel{\beta\alpha} - \cancel{\alpha\beta} - 1 + \alpha + \alpha\beta - \beta}{\alpha+\beta-2} \right] \\ &= \left[\frac{\beta-1}{\alpha+\beta-2} \quad \frac{\alpha-1}{\alpha+\beta-2} \right] = \gamma^*. \end{aligned}$$

ii. The stationary distribution ψ^* satisfies,

$$\psi^* = \psi^* \rho = \psi^* \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix}.$$

$$\Leftrightarrow [\psi_1^* \quad \psi_2^*] = [\psi_1^* \quad \psi_2^*] \begin{bmatrix} \alpha & 1-\alpha \\ 1-\beta & \beta \end{bmatrix}$$

$$\Leftrightarrow [\psi_1^* \quad \psi_2^*] = [\psi_1^* \alpha + \psi_2^*(1-\beta) \quad \psi_1^*(1-\alpha) + \psi_2^*\beta].$$

This gives a system of 3 linear equations,

$$\begin{aligned} a. \quad \psi_1^* \alpha + \psi_2^*(1-\beta) &= \psi_1^* & c. \quad \psi_1^* + \psi_2^* &= 1, \text{ from definition of probability measure} \\ b. \quad \psi_1^*(1-\alpha) + \psi_2^* \beta &= \psi_2^* \end{aligned}$$

$$\Rightarrow \psi_1^* \alpha + (1-\psi_1^*)(1-\beta) = \psi_1^* \Leftrightarrow \psi_1^* \alpha + 1 - \beta - \psi_1^*(1-\beta) = \psi_1^*$$

$$\Leftrightarrow (1-\beta) = \psi_1^*[1 + 1 - \beta - \alpha] \Leftrightarrow \frac{\beta-1}{\alpha+\beta-2} = \psi_1^*$$

$$\Rightarrow (1-\psi_2^*)(1-\alpha) + \psi_2^* \beta = \psi_2^* \Leftrightarrow (1-\alpha) = \psi_2^*[1 - \beta + 1 - \alpha] \Leftrightarrow \frac{\alpha-1}{\alpha+\beta-2} = \psi_2^*$$

$$\text{As such, } \psi^* = \begin{bmatrix} \frac{\beta-1}{\alpha+\beta-2} & \frac{\alpha-1}{\alpha+\beta-2} \end{bmatrix}.$$

i. By the Law of Iterated expectations,

$$E_0[y^t] = E_{y_0} \left[E_{0|y_0} [y^t | y_0] \right]. \text{ Since } y_0 = y^H, \\ = E_0 \left[E_{0|y_0} [y^t | y_0 = y^H] \right]. \text{ By definition of } E_{0|y_0},$$

$$E_{0|y_0} [y^t | y_0 = y^H] = \sum_s s P(y^t = s | y_0 = y^H), s \in \{y^U, y^E\}.$$

$$\Rightarrow E_0[y^t] = E_{y_0} \left[\sum_s s P(y^t = s | y_0 = y^H) \right]$$

$$= \sum_{y_0} P(y_0 = y^H) \cdot \left\{ \sum_s s P(y^t = s | y_0 = y^H) \right\}.$$

There are two cases,

i. if $y_0 = y^H = y^U$:

$$E_0[y^t] = y^U P(y^t = y^U | y_0 = y^U) + y^E P(y^t = y^E | y_0 = y^U)$$

We know from above that the conditional probabilities can be rewritten,

$$E_0[y^t] = y^U P_{11}^t + y^E P_{12}^t,$$

ii. if $y_0 = y^H = y^E$: Similarly, $E_0[y^t] = y^U P_{21}^t + y^E P_{22}^t$

Taken together,

$$E_0[y^t] = \begin{cases} y^U P_{11}^t + y^E P_{12}^t & \text{if } y_0 = y^U \\ y^U P_{21}^t + y^E P_{22}^t & \text{if } y_0 = y^E \end{cases}$$

2. a. [WTS: $\lim_{n \rightarrow \infty} (\mathcal{B}^n f)(x) = \frac{h(x)}{1-\alpha}$] Let $f = w$.

i. Consider $(\mathcal{B}w)(x) \equiv h(x) + \alpha w(x)$, $\alpha \in (0, 1)$. Iterating,

$$(\mathcal{B}w)(x) = h(x) + \alpha w(x)$$

$$(\mathcal{B}(\mathcal{B}w))(x) = h(x) + \alpha(h(x) + \alpha w(x)) = h(x) + \alpha h(x) + \alpha^2 w(x)$$

$$(\mathcal{B}(\mathcal{B}^2 w))(x) = h(x) + \alpha h(x) + \alpha^2 h(x) + \alpha^3 w(x)$$

⋮

$$(\mathcal{B}(\mathcal{B}^{n-1} w))(x) = h(x) \sum_{i=0}^{n-1} \alpha^i + \alpha^n w(x). \text{ Then,}$$

$$\lim_{n \rightarrow \infty} (\mathcal{B}^n w)(x) = \lim_{n \rightarrow \infty} \left[h(x) \sum_{i=0}^{n-1} \alpha^i + \alpha^n w(x) \right]$$

$$= h(x) \sum_{i=0}^{\infty} \alpha^i + 0 \quad \text{since } \alpha \in (0, 1). \text{ The}$$

sum of the geometric sequence $\sum_{i=0}^{\infty} \alpha^i = \frac{1}{1-\alpha}$. Thus,

$$\lim_{n \rightarrow \infty} (\mathcal{B}^n w)(x) = \frac{h(x)}{1-\alpha}. \quad \square$$

ii. A fixed point for \mathcal{B} satisfies $\mathcal{B}(v(x)) = v(x)$, where $v(x)$ is the fixed point. Let $v(x) = \frac{h(x)}{1-\alpha}$.

$$\text{Then, } \mathcal{B}(v(x)) = h(x) + \alpha \left[\frac{h(x)}{1-\alpha} \right]$$

$$= \frac{(1-\alpha)h(x) + \alpha h(x)}{1-\alpha} = \frac{h(x)}{1-\alpha}.$$

Thus, $v(x) = \frac{h(x)}{1-\alpha}$ is a fixed point for \mathcal{B} . \square

3. a. Let $d(f, g) = \sup_{x \in \mathbb{R}^L} |f(x) - g(x)|$. Let $x \in \mathbb{R}^L$. By definition,

$$-d(f, g) \leq f(x) - g(x) \leq d(f, g) \Rightarrow f(x) \leq g(x) + d(f, g) \quad \forall x. \quad \square$$

b. Let $f, g \in C(X)$ arbitrary: $d(f, g) = \sup_{x \in \mathbb{R}^L} |f(x) - g(x)| \geq 0$.

i. From part a, $f(x) \leq g(x) + d(f, g)$. By monotonicity,
 $B(f(x)) \leq B(g(x) + d(f, g))$. By discounting, $\exists \delta \in (0, 1)$ s.t.,

$$\leq B(g(x)) + \delta d(f, g). \text{ As such,}$$

$$(Bf)(x) \leq (Bg)(x) + \delta d(f, g).$$

ii. From part a, $g(x) \leq f(x) + d(f, g)$. By monotonicity,

$$(Bg)(x) \leq B(f(x) + d(f, g)). \text{ By discounting,}$$

$\exists \delta \in (0, 1)$ s.t. $\leq (Bf)(x) + \delta d(f, g)$, As such,

$$(Bg)(x) \leq (Bf)(x) + \delta d(f, g).$$

Therefore, $\forall f, g \in C(X)$, $\exists \delta \in (0, 1)$ s.t. $(Bf)(x) \leq (Bg)(x) + \delta d(f, g)$

$$\therefore (Bg)(x) \leq (Bf)(x) + \delta d(f, g). \quad \square$$

C. Consider $d(\mathcal{B}f, \mathcal{B}g) = \sup_{x \in \mathbb{R}^L} |(\mathcal{B}f)(x) - (\mathcal{B}g)(x)|$. Let $x \in \mathbb{R}^L$.
 From part b, $\exists \delta \in (0, 1)$ s.t.
 $(\mathcal{B}f)(x) \leq (\mathcal{B}g)(x) + \delta d(f, g) \Leftrightarrow (\mathcal{B}f)(x) - (\mathcal{B}g)(x) \leq \delta d(f, g)$
 Likewise, $(\mathcal{B}g)(x) - (\mathcal{B}f)(x) \leq \delta d(f, g)$
 $\Leftrightarrow (\mathcal{B}f)(x) - (\mathcal{B}g)(x) \geq -\delta d(f, g)$.
 Putting the above together,
 $-\delta d(f, g) \leq (\mathcal{B}f)(x) - (\mathcal{B}g)(x) \leq \delta d(f, g) \quad \forall x$
 $\Rightarrow \sup_{x \in \mathbb{R}^L} |(\mathcal{B}f)(x) - (\mathcal{B}g)(x)| \leq \delta d(f, g)$
 $\Rightarrow d(\mathcal{B}f, \mathcal{B}g) \leq \delta d(f, g)$. \square

4.a. Given $(Bf)(x) = \sup_{c \in [0, x]} \{ u(c) + \delta \mathbb{E}[f(\tilde{R}_{+1}(x-c) + \tilde{y}_{+1})] \} \forall x$,

i. B := Bellman operator, which operates on the function f , mapping it to a new function Bf

ii. f := value function, which gives the value attained by the objective function at its solution

iii. $\sup_{c \in [0, x]}$:= denotes we are maximizing total utility with respect to consumption, c

a. $c \in [0, x]$:= a constraint that indicates consumption can take any nonnegative value up to the amount x , which ~~likely~~ denotes the total wealth, which the DM can allocate to consumption in a given period; the liquidity constraint is implicit here since the agent cannot borrowing beyond available wealth

iv. $u(c)$:= instantaneous utility function, which gives utility from consuming c units in the current period

v. $\delta \mathbb{E}[f(\tilde{R}_{+1}(x-c) + \tilde{y}_{+1})]$:= discounted expected utility from the next period

a. $\delta \in (0, 1)$:= discount factor, which indicates how much the DM values future utility relative to current utility

b. \mathbb{E} := expectation, which reflects the fact $\tilde{R}_{+1}, \tilde{y}_{+1}$ are random variables

c. $\tilde{R}_{+1}(x-c)$:= random var. capturing the returns on assets from the current period to the next, where $x-c$ is the leftover liquidity of the agent after consuming c units in the current period

d. \tilde{Y}_{+1} := random variable capturing labor income in the next period

e. $f(\cdot)$:= value function evaluated at wealth available in the next period

b. The current period budget constraint is $x = s + c$, where s denotes savings. Wealth in the next period is,

$$\tilde{x}_{+1} = \tilde{R}_{+1}(x - c) + \tilde{Y}_{+1} \geq c_{+1}.$$

c. Let $f, g \in C(X)$ with $f(x) \leq g(x) \forall x \in X$. By definition,

$$(\mathcal{B}f)(x) = \sup_{c \in [0, x]} \left\{ u(c) + \delta \mathbb{E}[f(\tilde{R}_{+1}(x - c) + \tilde{Y}_{+1})] \right\} \quad \forall x. \text{ Since } f(x) \leq g(x) \forall x,$$

$$\leq \sup_{c \in [0, x]} \left\{ u(c) + \delta \mathbb{E}[g(\tilde{R}_{+1}(x - c) + \tilde{Y}_{+1})] \right\}$$

$$= (\mathcal{B}g)(x). \text{ Thus, monotonicity is satisfied.}$$

d. Let $f \in C(X)$, $a \geq 0$, $x \in X$ arbitrary. Consider

$$[\mathcal{B}(f+a)](x) = \sup_{c \in [0, x]} \left\{ u(c) + \delta \mathbb{E}[f(\tilde{R}_{+1}(x - c) + \tilde{Y}_{+1})] + a \right\}.$$

$$\text{Since } \mathbb{E}[a] = a, \quad = \sup_{c \in [0, x]} \left\{ u(c) + \delta \mathbb{E}[f(\tilde{R}_{+1}(x - c) + \tilde{Y}_{+1})] + \delta a \right\}$$

$$= \sup_{c \in [0, x]} \left\{ u(c) + \delta \mathbb{E}[f(\tilde{R}_{+1}(x - c) + \tilde{Y}_{+1})] \right\} + \delta a$$

$$= (\mathcal{B}f)(x) + \delta a.$$

As such, discounting is satisfied. \square

5. a. Consider the guess $V(k) = \gamma + \phi \ln k$. Then,

$$V(k) = \max_{k' \in \Gamma(k)} \{ \ln(k^\alpha - k') + \beta V(k') \}$$

$= \max_{k' \in \Gamma(k)} \{ \ln(k^\alpha - k') + \beta [\gamma + \phi \ln k'] \}$. The first-order condition w.r.t. k' is,

$$\frac{\partial}{\partial k'} \left\{ \ln(k^\alpha - k') \right\} + \frac{\partial}{\partial k'} \left\{ \beta [\gamma + \phi \ln k'] \right\} = 0$$

$$\Leftrightarrow -\frac{1}{k^\alpha - k'} + \frac{\beta \phi}{k'} = 0$$

$$\Leftrightarrow \frac{\beta \phi}{k'} = \frac{1}{k^\alpha - k'} \Leftrightarrow \beta [\phi k^\alpha - \phi k'] = k' \Leftrightarrow \frac{\beta \phi k^\alpha}{1 + \beta \phi} = k'$$

Separately, the Envelope theorem gives,

$$\frac{\partial u(k^\alpha - k')}{\partial k} = \frac{\partial V(k)}{\partial k} \Leftrightarrow \frac{\alpha k^{\alpha-1}}{k^\alpha - k'} = \frac{\phi}{k} \Leftrightarrow \alpha k^\alpha = \phi k^\alpha - \phi k' \Leftrightarrow \frac{(\phi - \alpha) k^\alpha}{\phi} = k'.$$

Putting these together gives,

$$\frac{\beta \phi k^\alpha}{1 + \beta \phi} = \frac{(\phi - \alpha) k^\alpha}{\phi} \Leftrightarrow \frac{\beta \phi}{1 + \beta \phi} = \frac{\phi - \alpha}{\phi}$$

$$\Leftrightarrow \beta \phi^2 = \phi - \alpha + \beta \phi^2 - \beta \phi \alpha \Leftrightarrow \alpha = \phi(1 - \beta \alpha) \Leftrightarrow \phi = \frac{\alpha}{1 - \beta \alpha}.$$

Returning to the F.O.C.,

$$k'(k) = \frac{\beta \phi k^\alpha}{1 + \beta \phi} = \frac{\beta \left[\frac{\alpha}{1 - \beta \alpha} \right] k^\alpha}{1 + \beta \left[\frac{\alpha}{1 - \beta \alpha} \right]} = \frac{\beta \alpha k^\alpha}{1 - \beta \alpha + \beta \alpha}$$

$$\Leftrightarrow \underline{k'(k) = \beta \alpha k^\alpha}.$$

Returning to the Bellman equation, we have,

$$V(k) = \max_{k' \in \Gamma(x)} \{ \ln(k^\alpha - k') + \beta V(k') \}, \text{ Substituting } V(k),$$

$$\Leftrightarrow \psi + \phi \ln(k) = \max_{k' \in \Gamma(x)} \{ \ln(k^\alpha - k') + \beta \{ \psi + \phi \ln(k') \} \}. \text{ Substituting } k'(k),$$

$$\Leftrightarrow \psi + \phi \ln(k) = \ln(k^\alpha - \beta^\alpha k^\alpha) + \beta \psi + \beta \phi \ln[\beta^\alpha k^\alpha].$$

$$\Leftrightarrow \psi + \phi \ln k = \alpha \ln(k) + \ln(1 - \beta^\alpha) + \beta \psi + \beta \phi [\ln(\beta^\alpha) + \alpha \ln(k)]$$

$$\Leftrightarrow \psi + \phi \ln k = \ln(1 - \beta^\alpha) + \beta \psi + \beta \phi \ln(\beta^\alpha) + (\beta \phi + 1) \alpha \ln(k)$$

$$\Leftrightarrow \psi - \beta \psi = \ln(1 - \beta^\alpha) + \beta \phi \ln(\beta^\alpha) + (\beta \phi + 1) \alpha \ln(k) - \phi \ln(k)$$

$$\Leftrightarrow \psi = \frac{1}{1-\beta} \left[\ln(1 - \beta^\alpha) + \beta \phi \ln(\beta^\alpha) + [(\beta \phi + 1) \alpha - \phi] \ln(k) \right]$$

$$= \frac{1}{1-\beta} \left[\ln(1 - \beta^\alpha) + \beta \phi \ln(\beta^\alpha) + [(\beta^\alpha - 1) \phi + \alpha] \ln(k) \right]$$

$$= \frac{1}{1-\beta} \left[\ln(1 - \beta^\alpha) + \beta \phi \ln(\beta^\alpha) + \left[\alpha - \frac{(1 - \beta^\alpha) \phi}{(1 - \beta^\alpha)} \right] \ln(k) \right]$$

$$\underline{\Leftrightarrow \psi = \frac{1}{1-\beta} \left[\ln(1 - \beta^\alpha) + \frac{\beta^\alpha}{1 - \beta^\alpha} \ln(\beta^\alpha) \right]}, (*)$$

As such, the functional equation is satisfied if $k_0 \in \Gamma(k)$ for

$$\psi = (*). \quad \square$$

b. We proceed with iterating the policy function,

$$k_1 = \alpha \beta k_0^\alpha, \quad k_2 = \alpha \beta k_1^\alpha = \alpha \beta [\alpha \beta k_0^\alpha]^\alpha = (\alpha \beta)^{1+\alpha} k_0^{\alpha^2},$$

$$k_3 = \alpha \beta k_2^\alpha = \alpha \beta [(\alpha \beta)^{1+\alpha} k_0^{\alpha^2}]^\alpha = (\alpha \beta)^{1+2+\alpha^2} k_0^{\alpha^3}$$

$$\Rightarrow k_t^* = (\alpha \beta)^{\sum_{i=0}^{t-1} \alpha^i} k_0^{\alpha^t}. \text{ Notice that } \sum_{i=0}^{t-1} \alpha^i = \frac{1-\alpha^t}{1-\alpha},$$

$$\Rightarrow k_t^* = (\alpha \beta)^{\frac{1-\alpha^t}{1-\alpha}} k_0^{\alpha^t}. \text{ Returning to,}$$

$$V(k_0) = \sum_{t=0}^{\infty} \beta^t \ln[(k_t^*)^\alpha - k_{t+1}^*] \text{ and substituting gives,}$$

$$= \sum_{t=0}^{\infty} \beta^t \ln \left[(\alpha \beta)^{\frac{\alpha(1-\alpha^t)}{1-\alpha}} k_0^{\alpha^{t+1}} - (\alpha \beta)^{\frac{1-\alpha^{t+1}}{1-\alpha}} k_0^{\alpha^{t+1}} \right]$$

$$= \sum_{t=0}^{\infty} \beta^t \left\{ \alpha^{t+1} \ln(k_0) + \frac{-\alpha^{t+1}}{1-\alpha} \ln(\alpha \beta) + \ln \left[(\alpha \beta)^{\frac{\alpha}{1-\alpha}} - (\alpha \beta)^{\frac{1}{1-\alpha}} \right] \right\}$$

$$= \sum_{t=0}^{\infty} (\beta \alpha)^t \alpha \left\{ \ln(k_0) + \frac{1}{1-\alpha} \ln(\alpha \beta) \right\} + \sum_{t=0}^{\infty} \beta^t \ln \left[(\alpha \beta)^{\frac{\alpha}{1-\alpha}} - (\alpha \beta)^{\frac{1}{1-\alpha}} \right]$$

$$= \frac{\alpha}{1-\alpha \beta} \left[\ln(k_0) - \frac{1}{1-\alpha} \ln(\alpha \beta) \right] + \frac{1}{1-\beta} \ln \left[(\alpha \beta)^{\frac{\alpha}{1-\alpha}} - (\alpha \beta)^{\frac{1}{1-\alpha}} \right]$$

$$= \frac{\alpha}{1-\alpha \beta} \ln(k_0) - \frac{\alpha}{(1-\alpha \beta)(1-\alpha)} \ln(\alpha \beta) + \frac{1}{1-\beta} \ln \left[(\alpha \beta)^{\frac{1}{1-\alpha}} \left[(\alpha \beta)^{\frac{\alpha-1}{1-\alpha}} - 1 \right] \right]$$

$$= \frac{\alpha}{1-\alpha \beta} \ln(k_0) - \frac{\alpha \ln(\alpha \beta)}{(1-\alpha \beta)(1-\alpha)} + \frac{1}{(1-\alpha)(1-\beta)} \ln(\alpha \beta) - \frac{1}{1-\beta} \ln \left[\frac{1}{\alpha \beta} - 1 \right]$$

$$= \frac{\alpha}{1-\alpha \beta} \ln(k_0) + \frac{-\alpha(1-\beta) + 1-\alpha \beta}{(1-\alpha \beta)(1-\alpha)(1-\beta)} \ln(\alpha \beta) + \frac{1}{1-\beta} \left\{ \ln \left[1 - \alpha \beta \right] - \ln(\alpha \beta) \right\}$$

$$= \frac{\alpha}{1-\alpha \beta} \ln(k_0) + \frac{1}{1-\beta} \left[\frac{1}{1-\alpha \beta} \ln(\alpha \beta) - \ln(\alpha \beta) + \ln \left[1 - \alpha \beta \right] \right]$$

$$= \frac{\alpha}{1-\alpha \beta} \ln(k_0) + \frac{1}{1-\beta} \left[\ln(\alpha \beta) \left[\frac{\alpha \beta}{1-\alpha \beta} \right] + \ln \left[1 - \alpha \beta \right] \right]$$

$= V(k_0)$ from our guess. Thus, the policy function is optimal. \square

C. We have,

$$(\bar{B}V)(k) = \sup_{k' \in \Gamma(k)} \left\{ \ln(k^\alpha - k') + \beta \left[\frac{\alpha \ln k'}{1-\alpha \beta} \right] \right\}.$$

F.O.C: $\frac{1}{k^\alpha - k} = \frac{\beta \alpha}{1-\alpha \beta} \cdot \frac{1}{k'} \Leftrightarrow (1-\alpha \beta)k' = \alpha \beta (k^\alpha - k')$
 $\Leftrightarrow k' = \alpha \beta k^\alpha.$

Then, $(\bar{B}V)(k) = \ln(k^\alpha - \alpha \beta k^\alpha) + \beta \left[\frac{\alpha \ln(\alpha \beta k^\alpha)}{1-\alpha \beta} \right]$
 $= \alpha \ln(k) + \ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \alpha \ln(k)$
 $= \ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) + \left[1 + \frac{\alpha \beta}{1-\alpha \beta} \right] \alpha \ln(k)$

$$\begin{aligned} (\bar{B}(\bar{B}V))(k) &= \ln(k^\alpha - \alpha \beta k^\alpha) + \beta \left[\ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) + \left[1 + \frac{\alpha \beta}{1-\alpha \beta} \right] \alpha \ln(k) \right] \\ &= \alpha \ln(k) + \ln(1-\alpha \beta) + \beta \ln(1-\alpha \beta) + \frac{\alpha \beta^2}{1-\alpha \beta} \ln(\alpha \beta) + \left[\beta + \frac{\alpha \beta^2}{1-\alpha \beta} \right] \alpha \ln(\alpha \beta k^\alpha) \\ &= (1+\beta) \ln(1-\alpha \beta) + \frac{\alpha \beta^2}{1-\alpha \beta} \ln(\alpha \beta) + \left[\alpha \beta + \frac{\alpha^2 \beta^2}{1-\alpha \beta} \right] \left[\alpha \ln(k) + \ln(\alpha \beta) \right] \\ &= (1+\beta) \ln(1-\alpha \beta) + \left[\alpha \beta + \frac{\alpha \beta^2}{1-\alpha \beta} + \frac{\alpha^2 \beta^2}{1-\alpha \beta} \right] \ln(\alpha \beta) + \left[1 + \alpha \beta + \frac{\alpha^2 \beta^2}{1-\alpha \beta} \right] \alpha \ln(k) \\ &= (1+\beta) \ln(1-\alpha \beta) + \left[1 + \beta \right] \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) + \left[\frac{1 - \alpha \beta + \alpha \beta - \alpha^2 \beta^2 + \alpha^2 \beta^2}{1-\alpha \beta} \right] \alpha \ln(k) \\ &= (1+\beta) \left[\ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) \right] + \frac{\alpha \ln(k)}{1-\alpha \beta} \end{aligned}$$

$$\begin{aligned} (\bar{B}^n V)(k) &= \sum_{i=1}^{n-1} \beta^i \left[\ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) \right] + \frac{\alpha \ln(k)}{1-\alpha \beta}. \quad \text{Notice, } \sum_{i=0}^{n-1} \beta^i = \frac{1-\beta^n}{1-\beta} \\ &= \frac{1-\beta^n}{1-\beta} \left[\ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) \right] + \frac{\alpha \ln(k)}{1-\alpha \beta}. \end{aligned}$$

Then, $\lim_{n \rightarrow \infty} (\bar{B}^n V)(k) = \frac{1-\beta}{1-\beta} \left[\ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) \right] + \frac{\alpha \ln(k)}{1-\alpha \beta}$, since $0 < \beta < 1$. As such,

$$\lim_{n \rightarrow \infty} (\bar{B}^n V)(k) = \frac{1}{1-\beta} \left[\ln(1-\alpha \beta) + \frac{\alpha \beta}{1-\alpha \beta} \ln(\alpha \beta) \right] + \frac{\alpha \ln(k)}{1-\alpha \beta}$$

= $V(k)$ from part a. \square

$$6. \text{ a. Given } V(x) = \max_{x' \in [0, x]} \left\{ u(x-x') + \mathbb{E} \left[e^{-\rho} V(e^{r+\sigma u - \frac{\sigma^2}{2}} x') \right] \right\}$$

i. $V(\cdot)$:= value function capturing the maximum utility with respect to wealth in the next period x'

ii. $\max_{x' \in [0, x]}$:= indicates we are maximizing the interior function w.r.t. x'

a. $x' \in [0, x]$ reflects choice of wealth in period $t+1$ cannot exceed wealth in period t , and must also be nonnegative

iii. $u(x-x')$:= instantaneous utility function capturing utility from consuming $c = x-x'$ units today i.e., wealth today less choice of wealth tomorrow; not a state variable since it only affects $V(x)$ through current period decisions

iv. $\mathbb{E} \left[e^{-\rho} V(e^{r+\sigma u - \frac{\sigma^2}{2}} x') \right]$:= collectively captures discounted value of consumption in the next period $t+1$ relative to period t

a. $e^{-\rho}$:= discount rate w.r.t. to impatience parameter ρ

b. $V(\cdot)$:= value function evaluated at wealth in the next period

c. $e^{r+\sigma u - \frac{\sigma^2}{2}} x'$:= captures the return on assets, which is a random variable

x. r := captures return on assets for period t

xx. σu := captures effect of i.i.d. random shock u , modulated by parameter σ , on returns in period t

xxx. $-\frac{\sigma^2}{2}$:= scaling parameter ensuring effects of shocks are unbiased

$$b. \text{ Given } V(x) = \max_{x' \in [0, x]} \left\{ u(x-x') + \mathbb{E} \left[e^{-\rho} V(e^{r+\sigma u - \frac{\sigma^2}{2}} x') \right] \right\}$$

the Envelope theorem gives,

$$\begin{aligned} \frac{\partial V(x)}{\partial x} &= \frac{\partial u(x-x')}{\partial x} \Leftrightarrow \frac{\partial}{\partial x} \left[\phi \frac{x^{1-r}}{1-r} \right] = \frac{\partial}{\partial x} \left[\frac{1}{1-r} (x-x')^{1-r} \right] \\ \Leftrightarrow \phi x^{-r} &= (x-x')^{-r} \Leftrightarrow \phi^{-\frac{1}{r}} x = x - x' \Leftrightarrow c = \underline{\phi^{-\frac{1}{r}} x} \\ \Rightarrow x-x' &= \phi^{-\frac{1}{r}} x \Leftrightarrow x' = \underline{x(1-\phi^{-\frac{1}{r}})}. \end{aligned}$$

Returning to the Bellman equation,

$$V(x) = \max_{x' \in [0, x]} \left\{ u(x-x') + \mathbb{E} \left[e^{-\rho} V(e^{r+\sigma u - \frac{\sigma^2}{2}} x') \right] \right\}$$

Substituting the guess for $V(x)$ gives,

$$\phi \frac{x^{1-r}}{1-r} = \max_{x' \in [0, x]} \left\{ u(x-x') + \mathbb{E} \left[e^{-\rho} \left[\phi \frac{(e^{r+\sigma u - \frac{\sigma^2}{2}} x)^{1-r}}{1-r} \right] \right] \right\}$$

Substituting for optimal $x' \in c$ gives,

$$\begin{aligned} \phi \frac{x^{1-r}}{1-r} &= \frac{1}{1-r} (\phi^{-\frac{1}{r}} x)^{1-r} + \mathbb{E} \left[e^{-\rho} \left[\phi \frac{(e^{r+\sigma u - \frac{\sigma^2}{2}} x(1-\phi^{-\frac{1}{r}}))^{1-r}}{1-r} \right] \right] \\ \Leftrightarrow \phi x^{1-r} &= \phi^{-\frac{1-r}{r}} x^{1-r} + x^{(1-r)(1-\phi^{-\frac{1}{r}})^{1-r}} e^{-\rho} \phi e^{(1-r)r - \frac{(r-1)\sigma^2}{2}} \mathbb{E} \left[e^{r(1-r)u} \right]. \end{aligned}$$

Since $u \sim N(0, 1)$, the MGF of u gives,

$$\begin{aligned} \phi x^{1-r} &= \phi^{-\frac{1-r}{r}} x^{1-r} + x^{(1-r)(1-\phi^{-\frac{1}{r}})^{1-r}} e^{-\rho} \phi e^{(1-r)r - \frac{(r-1)\sigma^2}{2}} e^{\frac{(1-r)\sigma^2}{2}}, \text{ with } x>0, \\ \Leftrightarrow \left(\phi - \phi^{-\frac{1-r}{r}} \right) &= (1-\phi^{-\frac{1}{r}})^{1-r} e^{-\rho} \phi e^{(1-r)(r - \frac{\sigma^2}{2})} e^{\frac{(1-r)^2 \sigma^2}{2}} \\ \Leftrightarrow \phi \left(1 - \phi^{(\frac{r-1}{r})-1} \right) &= (1-\phi^{-\frac{1}{r}})^{1-r} e^{-\rho} \phi e^{(1-r)(r - \frac{\sigma^2}{2})} e^{\frac{(1-r)^2 \sigma^2}{2}} \\ \Leftrightarrow (1-\phi^{-\frac{1}{r}})^{1-r} &= (1-\phi^{-\frac{1}{r}})^{(1-r)} e^{-\rho} e^{(1-r)(r - \frac{\sigma^2}{2})} e^{\frac{(1-r)^2 \sigma^2}{2}} \\ \Leftrightarrow (1-\phi^{-\frac{1}{r}})^r &= e^{-\rho} e^{(1-r)(r - \frac{\sigma^2}{2})} e^{\frac{(1-r)^2 \sigma^2}{2}} \end{aligned}$$

$$\Rightarrow r \ln(1 - \phi^{-\frac{1}{r}}) = -\rho + (1-r)(r - \frac{\sigma^2}{2}) + \frac{(1-r)^2 \sigma^2}{2}$$

$$\ln(1 - \phi^{-\frac{1}{r}}) = \frac{1}{r} \left[(1-r)r - \rho + (r-1+(1-r)^2) \frac{\sigma^2}{2} \right]$$

$$= \frac{1}{r} \left[(1-r)r - \rho + (r^2 - r) \frac{\sigma^2}{2} \right]$$

$\Rightarrow \ln(1 - \phi^{-\frac{1}{r}}) = \frac{1}{r} [(1-r)r - \rho] + (r-1) \frac{\sigma^2}{2}$. As such, the Bellman equation is satisfied for a particular value of ϕ . \square

c. Consider $E[\ln(\frac{c_{t+1}}{c_t})] = E\left\{\ln\left[\frac{\phi^{-\frac{1}{r}}x'}{\phi^{-\frac{1}{r}}x}\right]\right\} = E\left\{\ln\left[\frac{x'}{x}\right]\right\}$

From $x' = e^{r+\sigma u_t - \frac{\sigma^2}{2}}(x-c)$

$\Rightarrow E\left\{\ln\left[\frac{e^{r+\sigma u - \frac{\sigma^2}{2}}x(1-\phi^{-\frac{1}{r}})}{x}\right]\right\} = \ln(1-\phi^{-\frac{1}{r}}) + E[r + \sigma u - \frac{\sigma^2}{2}]$. Since $E[u] = 0$,

$= \ln(1-\phi^{-\frac{1}{r}}) + r - \frac{\sigma^2}{2}$. From part b,

$= \frac{1}{r} \left[(1-r)r - \rho \right] + \frac{1}{2} (r-1) \sigma^2 + r - \frac{\sigma^2}{2}$

$= \frac{1-r}{r} r - \frac{\rho}{r} + \frac{r\sigma^2}{2} - \frac{\sigma^2}{2} + r - \frac{\sigma^2}{2}$

$= \left(\frac{1-r}{r} + 1\right)r - \frac{\rho}{r} + \frac{r}{2}\sigma^2 - \sigma^2$

$= \frac{1}{r}[r - \rho] + \frac{r}{2}\sigma^2 - \sigma^2$. \square

$\frac{1-r+r}{r} = \frac{1}{r}$

d. Given $\sigma^2 = 0$, $E[\ln(\frac{c_{t+1}}{c_t})] = \frac{1}{r}(r - \rho)$. In words, the expected value of the growth rate of consumption in the $\sigma^2 = 0$ case is $\frac{1}{r}(r - \rho)$.

i. the expected value of the growth rate of consumption is increasing in r , since a higher return on the asset would encourage less consumption in the current period i.e., a lower $\ln(c_t)$ value, which increases $\ln(c_{t+1}) - \ln(c_t)$. Conversely, if ρ increases, the consumer places more value on consumption in the current period, hence a larger $\ln(c_t)$ value at a lower growth rate.

ii-iii. r in the denominator reflects the fact that if a consumer is particularly risk averse (high r), they consume more in the current period, leading to a lower growth rate. To illustrate, $\lim_{r \rightarrow \infty} E[\ln(c_{t+1}) - \ln(c_t)] = 0$ indicates that if the consumer is infinitely risk averse they consume their entire endowment in the current period leading to 0 consumption growth. As such, this parameter regulates the consumer's willingness to intertemporally substitute consumption.