

Econ 212a: Business Cycles

Lecture 2

RBC Model, part I

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- Last class, we discussed business-cycle regularities
 - business cycle = comovement of Y, C, I, N + their volatility patterns
- We started discussing the real business cycle (RBC) model
 - neoclassical growth model (NGM) + endogenous labor + technology shocks
 - we measured technology shocks as Solow residuals
- **Today:** Solve + calibrate RBC. How well does it capture the business cycle?

The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2004



Photo from the Nobel Foundation archive.

Finn E. Kydland

Prize share: 1/2



Photo from the Nobel Foundation archive.

Edward C. Prescott

Prize share: 1/2

“Kydland and Prescott demonstrated how **variations in technological development...** can lead to **short-run fluctuations.** In so doing, they offered a **new and operational paradigm for macroeconomic analysis** based on microeconomic foundations.”

RBC: planning problem

- Recall we wrote the production function as

$$Y_t = A_t F(K_{t-1}, (1+g)^t N_t)$$

Sometimes write $X_t \equiv (1+g)^t$. We also call A_t **TFP** (total factor productivity).

- A_t is stochastic. We think of it as following a *Markov process*, e.g. AR(1)

$$\log A_t = \rho \log A_{t-1} + \epsilon_t \quad (1)$$

- The RBC model in a nutshell...
 - take the NGM with endogenous labor supply
 - assume stochastic process for A_t , say (1)
 - see if macroeconomic aggregates (C_t, I_t, N_t, K_t) behave anything like in the data
- We start with the **planning problem**. We will later see that just like the NGM, the RBC model is frictionless, so planner's solution = comp. equilibrium.

Representing uncertainty

One key difference with NGM: uncertainty...

- Consider **state space** S
- One state $s_t \in S$ realized every period
 - In baseline model: TFP is function of state, $A = A(s_t)$
 - s_t follows a Markov chain, and A inherits its properties
 - $\pi(s_t|s_{t-1})$ transition matrix

- Histories of shocks $s^t = (s_0, s_1 \dots s_t) \in S^t$, probability:

$$\pi(s^t) \equiv \pi(s_t|s_{t-1})\pi(s_{t-1}|s_{t-2}) \cdots \pi(s_1|s_0)$$

- Agent have **rational expectations**: evaluate histories s^t with π
- A *consumption plan* is a set of functions $C_t(s^t)$, with $C_t: S^t \rightarrow \mathbb{R}$
 - similarly for all other variables

Planner's problem setup

- Planner's problem: choose $\{C_t(s^t), N_t(s^t), l_t(s^t), K_t(s^t)\}$ to solve

$$\begin{aligned} \max \quad & \sum_{t=0}^{\infty} \sum_{s^t \in S^t} \beta^t \pi(s^t) U(C_t(s^t), N_t(s^t)) \\ \text{s.t.} \quad & C_t(s^t) + l_t(s^t) = A(s_t) F(K_{t-1}(s^{t-1}), X_t N_t(s^t)) \\ & K_t(s^t) = (1 - \delta) K_{t-1}(s^{t-1}) + l_t(s^t) \end{aligned}$$

- Notes:
 - Closed economy with no government
 - Timing matters: capital K pre-determined in production F
 - Utility is decreasing in labor N (a “bad”, with $U_N < 0$)
 - sometimes written as a function of leisure $L = L^{\max} - N$

Simplifying notation...

- Sometimes, drop subscripts, eg write $C(s^t)$, $K(s^t)$, or drop s^t , write C_t , K_t
- Also, we write conditional expectation of consumption as

$$\mathbb{E}_t [C_{t+1}] = \mathbb{E} [C_{t+1}|s^t] = \mathbb{E}_t [C_{t+1}(s^{t+1})] = \sum_{s_{t+1}} \pi(s_{t+1}|s_t) C_{t+1}(s^{t+1})$$

and similarly for other variables

- For example, the objective function can then be written as

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(C_t, N_t) \right]$$

- An optimum can be characterized as solution to ...
 - Bellman equation
 - first order conditions (e.g. Euler equation)
- Start with first approach, for simplicity in special case $X_t = 1$.
- Then, discuss second approach.

Solution method 1: Bellman equation

- To set up Bellman, need to figure out the states of the model
 - economy at date t depends on entire history s^t ...
 - ... but only two objects really matter: current state s and capital $K_{t-1}(s^{t-1})$
- With s, K as states, Bellman is:

$$V(K, s) = \max_{C, N, K'} \left\{ U(C, N) + \beta \sum_{s'} \pi(s'|s) V(K', s') \right\} \quad (2)$$

$$C + K' = (1 - \delta) K + A(s) F(K, N)$$

- \rightarrow Solution is recursive and takes form of policy rules:

$$C = \Phi^C(K, s) \quad N = \Phi^N(K, s) \quad K' = \Phi^K(K, s)$$

- In special cases, can guess and verify analytical solution
- In other cases, can solve (2) on computer (we'll do something else)

Exercise: the Brock-Mirman model

- Assume that

$$F(K, N) = K^\alpha N^{1-\alpha} \quad \delta = 1 \quad U(C, N) = \log C - v(N)$$

Note: $\delta = 1$ is unrealistic! But very useful special case...

- Then guess $V(K, s) = a(s) + b \log K$ for some function $a(s)$, constant b
- Verifying the guess, we find policies:

$$K' = \Phi^K(K, s) = \alpha\beta A(s) F(K, \bar{N})$$

$$C = \Phi^C(K, s) = (1 - \alpha\beta) A(s) F(K, \bar{N})$$

$$N = \Phi^N(K, s) = \bar{N}$$

where \bar{N} is solution to $v'(\bar{N}) \bar{N} = \frac{1-\alpha}{1-\alpha\beta}$ (and $b = \frac{\alpha}{1-\alpha\beta}$)

- Labor is **constant**, even though marginal product $AF_N(K, N)$ moves. Why?

Solution method 2: First order conditions

- Many ways to derive them (eg Lagrangian)... here: **variational arguments**
- **Intratemporal optimality:** Work more in t , consume increased production

$$-U_N(C_t, N_t) = U_C(C_t, N_t) \cdot A_t X_t F_N(K_{t-1}, X_t N_t) \quad (3)$$

- **Intertemporal optimality:** Consume less in t , save, consume more in $t + 1$

$$U_C(C_t, N_t) = \beta \mathbb{E}_t [(A_{t+1} F_K(K_t, X_{t+1} N_{t+1}) + 1 - \delta) U_C(C_{t+1}, N_{t+1})] \quad (4)$$

- Finally, a **transversality condition:**

$$\lim_{t \rightarrow \infty} \beta^t \mathbb{E}_0 [U_C(C_t, N_t) K_{t-1}] = 0 \quad (5)$$

- With **resource constraints**, these are necessary and sufficient for optimum

$$C_t + I_t = A_t F(K_{t-1}, X_t N_t) \quad (6)$$

$$K_t = (1 - \delta) K_{t-1} + I_t \quad (7)$$

Two helpful objects

- Will “decentralize” the optimum from the planning problem as a competitive equilibrium next class
- Only then will “wages” and “interest rates” appear
- However, useful to define these objects already now:

$$W_t = A_t X_t F_N(K_{t-1}, X_t N_t) = MPL_t$$

$$R_t = 1 + r_t = A_t F_K(K_{t-1}, X_t N_t) + 1 - \delta = MPK_t + 1 - \delta$$

- W_t will be the real wage, R_t the gross ex-post return on capital

RBC Model: Calibration

- We'd like to know how well the RBC model describes business cycles
- **Calibration** = picking the model's **functional forms** and **parameter values**
- Main idea: Match
 - **long-run patterns** (e.g. growth rates, “big ratios”). Prescott's original approach.
 - **micro evidence** (more recent)
- Then we can simulate model and validate its business cycle predictions
- See Hansen–Heckman “the Empirical Foundations of Calibration” for more

Next: How to pick functional forms for the model, then parameters

Functional forms, part I: Impose balanced growth

- Our model has growing X_t . “Balanced growth” = $C_t/Y_t, K_t/Y_t, I_t/Y_t$ fluctuate around constant long-run trend, with constant hours per person N_t
- Along our optimum, this is only possible for a specific utility function

$$U(C, N) = \frac{[C \cdot e^{v(N)}]^{1-\nu} - 1}{1-\nu} \quad (8)$$

where $v(N)$ is a decreasing function of N .

- Known as **King-Plosser-Rebelo** (KPR) preferences.
 - great exercise to derive these! Hint: Set $A = 1$ in (3) and argue that $U(C, N)$ must be of the form $\mathcal{U}(Ce^{v(N)})$. Then use (4) to show (8).
- Case $\nu = 1$: *separable* preferences

$$U(C, N) = \log C - v(N) \quad (9)$$

Functional forms, part II: What is $v(N)$?

How should we choose $v(N)$? Define **Frisch elasticity** of labor

$$\text{Frisch} \equiv \left. \frac{d \log N}{d \log W} \right|_{U_C = \text{const}} = \left[\frac{d \log (-U_N)}{d \log N} \right]^{-1} \stackrel{\text{if } \nu=1}{=} \frac{v'(N)}{v''(N)N}$$

- Prescott's favorite specification (log C, log leisure)

$$U(C, N) = \log C + \psi \log(1 - N) \quad \Rightarrow \quad \text{Frisch} = \frac{1 - N}{N} \quad (10)$$

- More common today: constant-Frisch specification

$$U(C, N) = \log C - \psi \frac{N^{1+\phi}}{1+\phi} \quad \Rightarrow \quad \text{Frisch} = \phi^{-1} \quad (11)$$

- New Keynesian literature considers more general 'MaCurdy' prefs,

$$U(C, N) = \frac{C^{1-\sigma}}{1-\sigma} - \psi \frac{N^{1+\phi}}{1+\phi} \quad (12) \quad 15$$

Detrending the model

- With KPR preferences (8), we can detrend the model
- Define $c_t \equiv \frac{C_t}{X_t}$, $k_{t-1} \equiv \frac{K_{t-1}}{X_t}$, $i_t \equiv \frac{I_t}{X_t}$
- Then, given k_{-1} , $\{c_t, N_t, i_t, k_t\}_{t \geq 0}$ are solution to (check this!)

$$\begin{aligned} \max \quad & \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \tilde{\beta}^t U(c_t, N_t) \right] \\ \text{s.t.} \quad & c_t + i_t = A_t F(k_{t-1}, N_t) \\ & (1 + g) k_t = (1 - \delta) k_{t-1} + i_t \end{aligned}$$

where $\tilde{\beta} \equiv \beta (1 + g)^{1-\nu}$.

- It's **“as if” there was no long-run growth**, $X_t = 1$
 - except that $\tilde{\beta}$ replaces β and $1 + g$ shows up in capital accumulation
 - given that we pick $\tilde{\beta}$ anyway, common to just start with $g = 0$

Calibration of all parameters except ψ, β

- Cobb-Douglas production $F(k, N) = k^\alpha N^{1-\alpha}$, $\alpha \simeq \frac{1}{3}$
 - since labor share more or less constant
 - for depreciation rate δ King-Rebelo (KR) use 10% p.a. (on high end)
- Separable preferences (9). Traditional RBC literature uses (10)
 - more common today to use (11) to get plausible Frisch elasticity ϕ
 - ϕ turns out to be crucial to success of RBC model!
- Persistence ρ and std. dev. σ_ϵ of innovations to productivity

$$\log A_t = \rho \log A_{t-1} + \epsilon_t \quad \epsilon_t \sim N(0, \sigma_\epsilon^2)$$

- King-Rebelo find $\rho = 0.979$ and $\sigma_\epsilon = 0.0072$ (quarterly), growth $g = 1.6\%$ p.a.

Calibration or ψ, β : steady state optimality

Pin down ψ, β using long-run averages. Imagine no shocks, $A = 1$...

- From (3)–(7) at steady-state we have

$$v'(N)N = (1 - \alpha) \frac{Y}{C} \quad (13)$$

$$1 + g = \beta R = \beta \left(\alpha \frac{Y}{K} + 1 - \delta \right) \quad (14)$$

$$\frac{I}{Y} = (g + \delta) \frac{K}{Y} \quad (15)$$

- From (14), we get

$$\beta = \frac{1 + g}{1 + r} \simeq 0.988/\text{quarter} \quad \text{and} \quad \frac{K}{Y} = \frac{\alpha}{r + \delta} \simeq 8$$

- From (15) follows $\frac{I}{Y} \simeq 23\%$, and therefore $\frac{C}{Y} = 1 - \frac{I}{Y}$
- From (13) and Prescott's (10), we get $\psi = (1 - \alpha) \frac{1}{\frac{C}{Y}} \frac{1-N}{N}$. What is N ?

Calibration: final step

$$\psi = (1 - \alpha) \frac{1}{\frac{C}{Y}} \frac{1 - N}{N}$$

- Prescott calibration is $N = 0.2$
 - 16 hours per day, 7 days per week: 112 hours of time endowment
 - average weekly hours of employees = 35
 - employment-population ratio $\simeq 0.65$
 - so $N \simeq \frac{0.65 \times 35}{112} \simeq 0.2$
- Summary of benchmark calibration parameters (King-Rebelo)

g	β	ψ	α	δ	ρ	σ_{ϵ}
0.004	0.988	3.48	0.333	0.025	0.979	0.0072

$$F(K, N) = K^{\alpha} N^{1-\alpha} \quad U(C, N) = \log C + \psi \log(1 - N)$$

RBC Model: Results

Results

- Simulate artificial data from model, HP filter it, compare second moments

Table 3
Business cycle statistics for basic RBC model^{a,b}

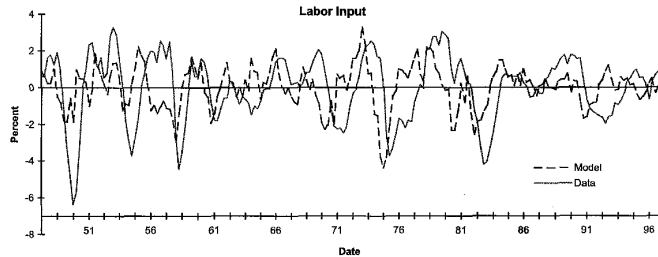
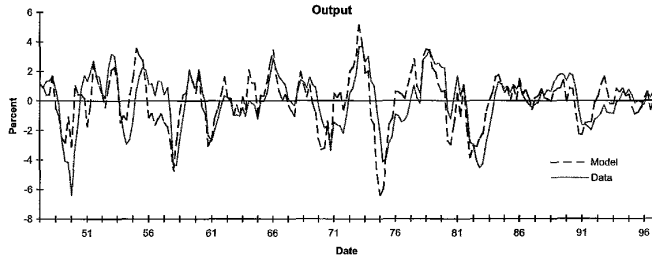
	Standard deviation	Relative standard deviation	First-order autocorrelation	Contemporaneous correlation with output
<i>Y</i>	1.39	1.00	0.72	1.00
<i>C</i>	0.61	0.44	0.79	0.94
<i>I</i>	4.09	2.95	0.71	0.99
<i>N</i>	0.67	0.48	0.71	0.97
<i>Y/N</i>	0.75	0.54	0.76	0.98
<i>w</i>	0.75	0.54	0.76	0.98
<i>r</i>	0.05	0.04	0.71	0.95
<i>A</i>	0.94	0.68	0.72	1.00

Table 1
Business cycle statistics for the US Economy

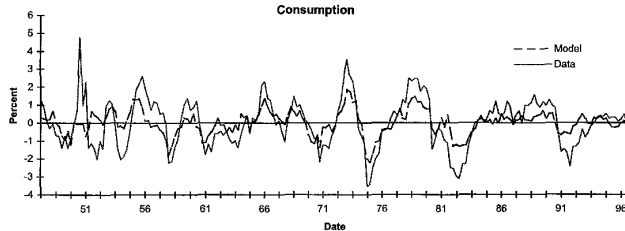
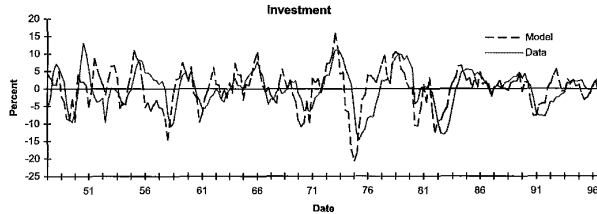
	Standard deviation	Relative standard deviation	First-order autocorrelation	Contemporaneous correlation with output
<i>Y</i>	1.81	1.00	0.84	1.00
<i>C</i>	1.35	0.74	0.80	0.88
<i>I</i>	5.30	2.93	0.87	0.80
<i>N</i>	1.79	0.99	0.88	0.88
<i>Y/N</i>	1.02	0.56	0.74	0.55
<i>w</i>	0.68	0.38	0.66	0.12
<i>r</i>	0.30	0.16	0.60	-0.35
<i>A</i>	0.98	0.54	0.74	0.78

- Surprisingly good performance for such a simple model?
 - Prescott: “account for more than half of the fluctuations in the postwar period, with a best point estimate near 75%” $[(\frac{1.39}{1.81})^2 = 0.77]$
- Another way to look at it: feed actual Solow residual into model & compare

Actual vs simulated series



Actual vs simulated series



Main takeaways from exercise

- Success:
 - I 3 times more volatile than Y
 - C smoother than Y (too smooth?)
 - all quantities comove with output as in data (correlation too high?)
 - Failures:
 - too little *amplification*: model $\frac{\sigma_Y}{\sigma_A} = 1.47$, vs data $\frac{\sigma_Y}{\sigma_A} = 1.94$
 - The model's N does not move enough, and leads N in the data
 - prices (W and r) are much too procyclical
 - Does RBC model do well **for the right reasons** ?
 - Summers 1986: *“Extremely bad theories can predict remarkably well...”*
(his examples: Ptolemaian astronomy, Lamarckian Biology)
- How can we know? Let's study the “transmission mechanism”

The RBC impulse response

Law of motion and impulse response

- Fundamental concept: the *impulse responses* of model to shocks (here, ϵ_t)
- Recall the policy functions of the model are $C_t = \Phi^C(K_{t-1}, A_t)$, $K_t = \Phi^K(K_{t-1}, A_t)$, where the Φ^C, Φ^K depend on model parameters
- Given these, the **state-space law of motion** of the model is

$$K_t = \Phi^K(K_{t-1}, A_t)$$

$$C_t = \Phi^C(K_{t-1}, A_t)$$

$$\log A_t = \rho \log A_{t-1} + \epsilon_t$$

- Definition: the **impulse response** of C to A is the expected time path of C , following an innovation to the process for A , starting from the steady state
- We can obtain this impulse response by simulating the state-space LOM and taking averages across paths of $\{\epsilon_t\}$ to get $\mathbb{E}[C_t]$. It's pretty complicated!

Linear state-space law of motion

- Loglinearizing the policy functions, denoting log deviations from steady state $k_t = dK_t/K = d \log K_t$, etc, we get:

$$\begin{aligned}k_t &= \eta_{kk}k_{t-1} + \eta_{ka}a_t \\c_t &= \eta_{ck}k_{t-1} + \eta_{ca}a_t \\a_t &= \rho a_{t-1} + \epsilon_t\end{aligned}\tag{LOM}$$

where $\eta_{kk} = \frac{\partial \Phi^K}{\partial K}$, $\eta_{ck} = \frac{K}{C} \frac{\partial \Phi^C}{\partial K}$, etc, and ϵ_t is iid with $\mathbb{E}[\epsilon_t] = 0$, $\text{Var}(\epsilon_t) = \sigma_\epsilon^2$

- This is known as the **linear state-space law of motion**
- In this linearized model, the impulse response of c to a is:

$$\text{irf}_t^c \equiv \mathbb{E}_0[c_t | \epsilon_0 = 1, k_{-1} = 0, a_{-1} = 0] - \mathbb{E}_0[c_t | \epsilon_0 = 0, k_{-1} = 0, a_{-1} = 0] \quad (16)$$

This is *much* simpler to get!

Obtaining the IRF in the linear model and certainty equivalence

- Why? Applying \mathbb{E}_0 to (LOM), we get:

$$\begin{aligned}\mathbb{E}_0[k_t] &= \eta_{kk}\mathbb{E}_0[k_{t-1}] + \eta_{ka}\mathbb{E}_0[a_t] \\ \mathbb{E}_0[c_t] &= \eta_{ck}\mathbb{E}_0[k_{t-1}] + \eta_{ca}\mathbb{E}_0[a_t] \\ \mathbb{E}_0[a_t] &= \rho\mathbb{E}_0[a_{t-1}] + \epsilon_0\mathbf{1}_{t=0}\end{aligned}\tag{PF-LOM}$$

This is a system of regular (i.e. non-stochastic) difference equations

- Using our definition (16), we obtain:

$$\text{irf}_t^c \equiv \mathbb{E}_0[c_t|\epsilon_0 = 1] - \mathbb{E}_0[c_t|\epsilon_0 = 0] = \mathbb{E}_0[c_t|\epsilon_0 = 1]$$

→ can get irf_t^c by simulating (PF-LOM) **once** given $k_{-1} = 0$, $a_{-1} = 0$, and $\epsilon_0 = 1$

- In words: the irf_t^c is the deterministic solution to (LOM), assuming that productivity a_t realizes at its expected value as of date 0, $\mathbb{E}_0[a_t|\epsilon_0 = 1] = \rho^t$
- This property is called **certainty equivalence**.

MA(∞) representation of the solution

- An alternative route to irf_t^c : obtain the MA(∞) representation of (LOM)
- Iterating $a_t = \rho a_{t-1} + \epsilon_t$ backward, we get $a_t = \sum_{j=0}^{\infty} \rho^j \epsilon_{t-j}$, the MA(∞) representation of productivity on its innovations.
- Then, iterating (LOM) backward, we get

$$c_t = \sum_{j=0}^{\infty} \gamma_j^c \epsilon_{t-j} \quad (\text{MA})$$

this is the **MA(∞) representation of consumption** on the innovations to a

- We have the following important result:

$$\text{irf}_t^c = \gamma_t^c$$

with a linear LOM, impulse response and MA(∞) coeffs are the same thing

Proof that impulse response and MA coefficients are the same

- Why? Let's calculate

$$\mathbb{E}_0 [c_t | \{\epsilon_0, \epsilon_{-1}, \dots\}] = \sum_{j=0}^{\infty} \gamma_j^c \mathbb{E}_0 [\epsilon_{t-j}] = 0 + \dots + 0 + \gamma_t^c \epsilon_0 + \gamma_{t+1}^c \epsilon_{-1} + \dots$$

so, since e.g. $\{\epsilon_{-1}, \epsilon_{-2}, \dots\} = \{0, 0, \dots\}$ gives us the steady state, we find

$$\mathbb{E}_0 [c_t | \epsilon_0, k_{-1} = 0, a_{-1} = 0] = \gamma_t^c \epsilon_0$$

- So, applying our definition:

$$\begin{aligned} \text{irf}_t^c &= \mathbb{E}_0 [c_t | \epsilon_0 = 1, k_{-1} = 0, a_{-1} = 0] - \mathbb{E}_0 [c_t | \epsilon_0 = 0, k_{-1} = 0, a_{-1} = 0] \\ &= \gamma_t^c \times 1 - \gamma_t^c \times 0 \\ &= \gamma_t^c \end{aligned}$$

Voilà!

Impulse response and MA coefficients

- Bottom line: so far, we have two equivalent ways of obtaining irf's:
 1. Iterate forward on (LOM) from date 0, assuming all future ϵ_t 's realize at 0
 2. Get the MA(∞) representation
- Neither requires simulations. Instead, we can use the irf's to simulate c_t !
 - How? Draw paths for $\{\epsilon_{t-j}\}$, then simulate paths for c_t by applying (MA)
- In fact, to obtain 2nd moments of the model, we don't even need simulation
 - Instead, we can directly use (MA) again, e.g.

$$\text{Cov}(c_t, c_{t+k}) = \sigma_\epsilon^2 \sum_{j=0}^{\infty} \text{irf}_j^c \text{irf}_{j+k}^c$$

e.g. $\text{Var}(c_t)$ is just σ_ϵ^2 times the area under the squared impulse response of c

- We can then use these moments to estimate the model parameters! (eg by SMM, maximum likelihood, Bayesian estimation with priors, etc.)

Nonlinear perfect-foresight approach

- There is a third useful way to get the irf's, which is what we will use
- Idea: assume perfect foresight from the very beginning. Then, (3)–(7) read

$$-U_N(C_t, N_t) = U_C(C_t, N_t) \cdot A_t F_N(K_{t-1}, N_t)$$

$$U_C(C_t, N_t) = \beta (A_{t+1} F_K(K_t, N_{t+1}) + 1 - \delta) U_C(C_{t+1}, N_{t+1})$$

$$C_t + K_t - (1 - \delta) K_{t-1} = A_t F(K_{t-1}, N_t)$$

- Starting from steady state K_{-1} and a given known path for $\{A_t\}_{t=0}^{\infty}$, these equations (plus the TVC) give us a unique path for C_t , which we can write

$$C_t(\{A_s\}_{s=0}^{\infty})$$

- For any $\sigma > 0$, let us define $c_t^{NL}(\sigma) \equiv \log C_t(\{\exp(\sigma \rho^s)\})$
- This is a “nonlinear impulse response”. **Result:** we have $\text{irf}_t^c = (c_t^{NL})'(0)$

- This result implies:

$$\text{irf}_t^c = \frac{d \log C_t(\{\exp(\sigma \rho^s)\})}{d\sigma} = \frac{A}{C} \sum_{s=0}^{\infty} \frac{\partial C_t}{\partial A_s} \rho^s$$

- Let $G_{t,s} \equiv \frac{\partial C_t}{\partial A_s}$. This is a “sequence-space Jacobian”. Write as matrix \mathbf{G}^c , then

$$\begin{pmatrix} \text{irf}_0^c & \text{irf}_1^c & \text{irf}_2^c & \cdots \end{pmatrix}' = \frac{A}{C} \mathbf{G}^c \begin{pmatrix} 1 & \rho & \rho^2 & \cdots \end{pmatrix}'$$

- More generally, if the $\text{MA}(\infty)$ for TFP is $a_t = \sum_{j=0}^{\infty} \gamma_j^a \epsilon_{t-j}$ then we have

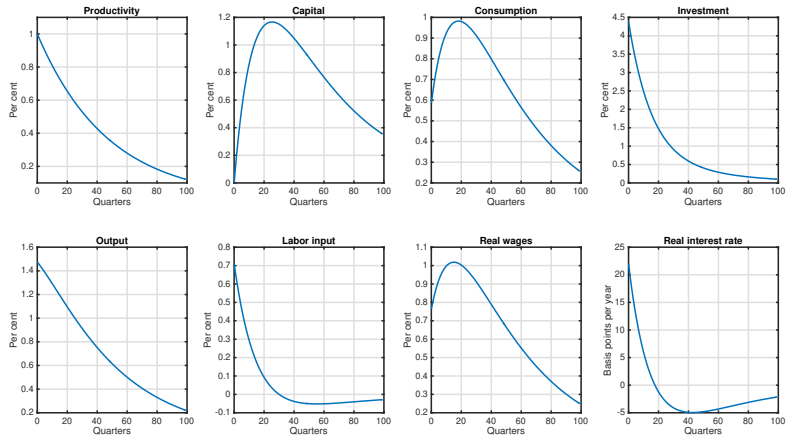
$$\begin{pmatrix} \text{irf}_0^c & \text{irf}_1^c & \text{irf}_2^c & \cdots \end{pmatrix}' = \frac{A}{C} \mathbf{G}^c \begin{pmatrix} \gamma_0^a & \gamma_1^a & \gamma_2^a & \cdots \end{pmatrix}'$$

The \mathbf{G} matrix maps one MA representation into another! Bottom line:

$\mathbf{G} \rightarrow \text{irf} \rightarrow \text{MA} \rightarrow \text{simulations, second moments, estimation....}$

- How do we get \mathbf{G} ? Analytically, or numerically with SSJ (cf notes+section)

Impulse response to technological innovation (KR fig 10)



- Q: Why does labor increase? Why does consumption increase?
- See next class!