Computational Methods for Macroeconomics (Part II) Lecture 4: Heterogeneous firm models

Hanbaek Lee

University of Cambridge

March 15, 2022

Background: Heterogeneous firm models

- Prescott and Kydland (1982): Time-to-build for capital investment
- Hopenhayn (1992): stationary equilibrium distribution of firm-level allocations: entry, exit, and size.
- Capital adjustment cost
 - Abel (1983): Convex capital adjustment cost
 - Cooper and Haltiwanger (2006): "The Nature of Capital Adjustment Costs"

Lumpy investment

- Caballero and Bertola (1994), Caballero and Engel (1999), Abel and Eberly (2002)
- Khan and Thomas (2008), Khan and Thomas (2003): Strong GE effect
- Bachmann et al. (2013), Winberry (2021), Koby and Wolf (2020), Lee (2022): Weak GE effect
- Heavy tail distribution
 - Gabaix (2009): A heavy-tail of the firm size distribution
- Financial friction
 - Bernanke and Gertler (1989), Kiyotaki Moore (1997), Brunnermeier and Sannikov (2014)

Background: Khan and Thomas (2008)

- Khan and Thomas (2008) studies heterogeneous establishments (c.f., firms) under the aggregate productivity fluctuations.
- ► An improved investment-to-capital distribution compared to Khan and Thomas (2003).
- Establishment-level nonlinear investment dynamics: (S, s) cycle.
- ► Macro-level log-linear investment dynamics: strong general equilibrium effect.
- Basic ingredients:
 - Heterogeneous idiosyncratic productivity process under the incomplete market (time-to-build).
 - Aggregate TFP fluctuations (Krusell and Smith, 1997).
 - The fixed cost, $\xi \sim_{iid} Unif[0, \overline{\xi}]$: smoothing the kink of the value function.
 - A small-scale investment is allowed, which is not subject to a fixed cost.
 - Value function normalization steps.
 - Non-trivial market clearing condition.
 - Representative household and competitive factor market.

Model

Hanbaek Lee (University of Cambridge)

Lecture 4: Heterogeneous firm models

Establishment-level production

- At the beginning of period t, a firm i is given with $(k_{it}, z_{it}; S_t)$:
 - $-k_{it}$: Pre-determined establishment-level capital stock.
 - z_{it} : Establishment-level idiosyncratic productivity (AR(1) process).
 - $S_t = \{A_t, \Phi_t\}$: A_t is aggregate productivity (AR(1) process); Φ_t is the distribution of individual establishments.
- Cobb-Douglas production function with DRS ($\alpha + \gamma < 1$) where labor demand is contemporaneously determined:

$$f(k_{it}, z_{it}; S_t) = A_t z_{it} (k_{it})^{\alpha} n_{it}^{\gamma}$$

- Operating profit due to DRS: $\pi(k_{it}, z_{it}; S_t) = \max_{n_{it}} f(k_{it}, z_{it}; S_t) w_t n_{it}$
- Operating profit = Dividends (D_{it}) + Investment (I_{it})
- The objective function is maximizing the firm value:

$$J_{it} = \max_{\{D_{it}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \frac{1}{R_t} D_{it}$$

	Model oo●ooooooo	Computation 000000000	Concluding remarks	
Establishmen	t-level investment			
 A firm needs 	to decide k_{it+1} by choosing I_{it} .			
$k_{it+1} = (1-\delta)k_{it} + I_{it}$				

- Two options in the investment scale: large/small
- If $I_{it} \in \Omega(k_{it}) := [\nu k_{it}, \nu k_{it}]$, then there is no fixed cost. ($\nu < \delta$)
- ► If $I_{it} \notin \Omega(k_{it}) := [\nu k_{it}, \nu k_{it}]$, then a fixed cost $\xi_{it} \sim_{iid} Unif([0, \overline{\xi}])$: Why?
- Role of fixed adjustment cost:
 - Inaction period: no lumpy investment inside the (S, s) cycle.
 - Large adjustment: Jumping from s to S.
- No convex adjustment cost in Khan and Thomas (2008) but Winberry (2021) introduces a convex adjustment cost.
- Role of convex adjustment cost:
 - When your productivity jumps from 1 to 1.5, the unconstrained optimal level of future capital jumps identically across the different size of firms.
 - Without the convex adjustment cost, the capital stock of small firms can immediately jump up to the optimal level, being a sudden large firm.

Introduction	Model	Computation	Concluding remarks	
	00000000			
Household				

A representative household consumes, supplies labor, and saves.

$$egin{aligned} V(a;S) &= \max_{c,a',l_H} & log(c) - \eta l_H + eta \mathbb{E} V(a';S') \ & ext{s.t.} \ c + \int \Gamma_{S,S'} q(S,S') a(S') dS' &= w(S) l_H + \int a(S) dS \ & ext{ } G_{\phi}(S) &= \Phi', \quad G_A(A) &= A', \quad S &= \{\Phi,A\} \end{aligned}$$

- **>** *a*: an equity portfolio, Φ: distribution of firms
 - A: aggregate productivity, c: consumption
 - a': a state-contingent future saving portfolio, I_H : labor supply (indivisible)
 - q: state-contingent bond price, w: wage
- Household is holding the equity of firms as their wealth.
- Stochastic discount factor:

$$q(S,S') = \beta \frac{C(S)}{C(S')}$$

Khan and Thomas (2008) defines $p(S) := \frac{1}{C(S)}$, which will be extensively used after the normalization.

Introduction 00	Model oooo●oc	0000	Computation 000000000	Concluding remark
Recur	sive formulation			
	$J(k,z;S)=-\pi(k,z;S)+$	$(1-\delta)k + \int_{0}^{\overline{\xi}}$	$\max{\{R^*(k,z;S)-w(S)\xi,R^c(k)\}}$	$,z;S)\} dG_{\xi}(\xi)$
	$R^*(k, z; S) = \max_{k'}$	-k'-c(k,k')	$+\mathbb{E}m(S,S')J(k',z';S')$	
	$R^{c}(k,z;S) = \max_{k^{c}-(1-\delta)k\in\Omega(k)}$	$-k^{c}-c(k,k^{c})$	$)+\mathbb{E}m(S,S')J(k^{c},z';S')$	
	(Operating profit)	$\pi(z,k;S)$	$:= \max_{n_d} zAk^{\alpha} n_d^{\gamma} - w(S)n_d \ (n_d:$	labor demand)
	(Constrained investment)	$I^c\in \Omega(k)$	$:= [-k u, k u] (u < \delta)$	
	(Convex adjustment cost)	c(k,k') :=	$=\left(\mu'/2 ight)\left((k'-(1-\delta)k)/k ight)^2k$	r
		(Khan and	d Thomas (2008): $\mu=$ 0)	
	(Idiosyncratic productivity)	$z' = G_z(z$) (AR(1) process)	
	(Stochastic discount factor)	m(S,S') =	$= \beta \left(C(S) / C(S') \right)$	
	(Aggregate states)	$S = \{A, \Phi\}$)}	
	(Aggregate law of motion)	$\Phi' := H(S)$	5), $A' = G_A(A)$ (AR(1) process)	١,

Hanbaek Lee (University of Cambridge)

Model	Computation	Concluding remarks
00000000		

National accounting

▶ National account tracking is important for the efficient GE computation.

$$Y = C + I = C + (\tilde{I} + Adj.Cost)$$

$$C = Y - I$$

$$= (\Pi + W * L) - I$$

$$= (\Pi - I) + W * L$$

$$= \underbrace{D}_{\text{Dividend income}} + \underbrace{W * L}_{\text{Labor income}}$$

- Therefore, consumption is total dividends plus total labor expenses.
- After obtaining the distribution of firms, we compute total dividend and labor expense. Then, we obtain the consumption.
- Why does consumption matter? It determines w(S) and q(S, S'): next slide.

Non-trivial market clearing condition

From the intra-temporal labor supply optimality condition:

 $\eta = \lambda(\mu(S); S)w(S)$ = p(S)w(S)

- Therefore, if p(S) is known, then w(S) is determined. (What if GHH utility?)
- We still need to know SDF, q(S, S'), to solve the problem.
- However, the following slide's normalization eases the problem: p(S) is the only price!
- Where is p(S) is determined?
 - There is no closed-form to determine P(S).
 - The notorious internal loop:
 - 1. Guess p(S).
 - 2. Using the given distribution, $\Phi(S)$ compute the aggregate consumption c(S) = D(S) + W(S) * L(S).
 - 3. Compute $p^{update}(S) = 1/c(S)$, and repeat the steps until $||p(S) p^{update}(S)|| < tol$

Introduction 00	Model 0000000●00		Computation 000000000	Concluding remarks 00
Normalizatio	n			
Multiply $p(S) = 1$	/C(S) on the both sides	of the value fund	ction identity.	
p(S)J(k,z;S)=p	$p(S)(\pi(k,z;S) + (1-\delta)k)$	$k) + \int_0^{\overline{\xi}} \max \{ p($	$(S)R^*(k,z;S) - p(S)w(S)$	$\xi, p(S)R^{c}(k,z;S) dG_{\xi}(\xi)$
Define $(\widetilde{J},\widetilde{R}^{*},\widetilde{R}^{c})$	as follows:			
$\widetilde{J}(k,z;S)$:= p(S)J(k,z;S)			
$\widetilde{R}^*(k,z;S)$	$:= p(S)R^*(k,z;S)$	$= \max_{k'} (-k' -$	$c(k,k'))p(S) + \mathbb{E}p(S)q(S)$	(5, S')J(k', z'; S')
		$= \max_{k'} (-k' -$	$+ c(k,k'))p(S) + \mathbb{E} eta p(S')$	I(k', z'; S')
		$= \max_{k'} (-k' -$	$c(k,k'))p(S) + \mathbb{E}_{eta}\widetilde{J}(k',z)$	r'; S')
$\widetilde{R}^{c}(k,z;S)$	$:= p(S)R^{c}(k,z;S)$	$= \max_{\substack{k^c - (1 - \delta k) \in \Omega(k)}}$	$(-k^{c}-c(k,k^{c}))p(S)+$	$\mathbb{E}_{\beta}\widetilde{J}(k^{c},z';S')$
It is necessary to c	heck whether the recursi	ve form is preser	ved for the normalized val	ue functions.
\tilde{a}		$\int_{\varepsilon} \int_{\varepsilon} \int_{\varepsilon$		

 $J(k, z; S) = p(S)(\pi(k, z; S) + (1 - \delta)k) + \int_{0} \max \left\{ R^{*}(k, z; S) - P(S)w(S)\xi, R^{c}(k, z; S) \right\} dG_{\xi}(\xi)$ Thanks to this normalization, we only need to track p(S) instead of q(S, S').

Hanbaek Lee (University of Cambridge)

Smoothing the kink and the extensive margin

$$\int_{0}^{\hat{\xi}} \max \left\{ R^{*}(k,z;S) - w(S)\xi, R^{c}(k,z;S)
ight\} dG_{\xi}(\xi)$$

(1)

Then, there exists $\xi^*(k, z; S)$ such that

$$egin{aligned} R^*(k,z;S) &- w(S)\xi > R^c(k,z;S) & ext{if } \xi < \xi^*(k,z;S) \ R^*(k,z;S) &- w(S)\xi \leq R^c(k,z;S) & ext{if } \xi \geq \xi^*(k,z;S) \end{aligned}$$

Especially, $\xi^*(k, z; S) = \frac{R^*(k, z; S) - R^c(k, z; S)}{w(S)}$ is the closed-form characterzation.

- In the support of ξ, [0, ξ*) corresponds to large-scale investment and [ξ*, ξ̄] corresponds to small-scale investment: define ψ(k, z; S) := min{ξ*(k,z;S),ξ̄}/ζ̄
- With probability $\psi(k, z; S)$, a firm makes a large-scale investment.
- Eq (1) becomes a linear combination form: No Kink! (c.f., Discrete choice model)

$$\psi(k,z;S)\left(R^{*}(k,z;S)-w(S)\frac{\xi^{*}(k,z;S)}{2}\right)+(1-\psi(k,z;S))(R^{c}(k,z;S)).$$

Hanbaek Lee (University of Cambridge)

Recursive competitive equilibrium

 $(g_c, g_a, g_{l_H}, g_{k^*}, g_{k^c}, g_{\xi^*}, g_{n_d}, \widetilde{V}, \widetilde{J}, \widetilde{R}^*, \widetilde{R}^c, p, w)$ is a recursive competitive equilibrium if the following conditions are satisfied.

- 1. $g_c, g_{IH}, \widetilde{V}$ and g_a , solves the household's problem.
- 2. $g_{k^*}, g_{k^c}, g_{\xi^*}, g_{n_d}, \widetilde{J}, \widetilde{R}^*$, and \widetilde{R}^c solve a firm's problem.
- 3. Market Clearing:

$$\begin{array}{ll} \text{(Labor Market)} & g_{lH}(\Phi;S) = \int \left(g_{n_d}(k,z;S) + \left(\frac{g_{\xi^*}(k,z;S)}{\overline{\xi}} \right) \left(\frac{g_{\xi^*}(k,z;S)}{2} \right) k^{\zeta} \right) d\Phi \\ \text{(Product Market)} & g_c(\Phi;S) = \int \left(zAk^{\alpha}g_{n_d}(k,z;S)^{\gamma} \\ & - \left((g_{k^*}(k,z;S) - (1-\delta)k) + c(k,g_{k^*}(k,z;S)) \right) \frac{g_{\xi^*}(k,z;S)}{\overline{\xi}} \\ & - \left((g_{k^c}(k,z;S) - (1-\delta)k) + c(k,g_{k^c}(k,z;S)) \right) \frac{1 - g_{\xi^*}(k,z;S)}{\overline{\xi}} \right) d\Phi \end{array}$$

4. Consistency Condition: • Detail

Computation

Hanbaek Lee (University of Cambridge)

Lecture 4: Heterogeneous firm models

Model 000000000	Computation ○●○○○○○○○○	Concluding remarks

Roadmap

The following is the roadmap for computation section.

- 1. Set the parametric law of motion: assumption
- 2. Guess the parameters: $\#(S) \times 2 \times 2$
- 3. Solution (optimization)
 - VFI/PFI/EGM/Projection method
 - Interpolation
- 4. Simulation and internal loop for price p
 - Simulation
 - Aggregation
 - Update p until convergence
- 5. Update the parameters
- 6. After convergence, verify the assumption
- After this, we will talk about more recent developments.

Basic setup

The basic steps.

- Set directories
- Set parameters (might be a function argument)

Then, two important steps follow.

- Setting grid points.
 - Individual capital grid
 - Aggregate capital grid: this grid can be sparse (5 \sim 10 grids)
- Discretizing idiosyncratic shock process (Markov chain)
 - Tauchen method
 - Rouwenhorst method

Parametric law of motion

There are two layers of choices:

First, we need to set what are sufficient statistics to characterize the dynamics of the individual state distribution.

- A good candidate is the first moment of the endogenous individual state.
- As in Krusell and Smith (1998), by tracking only K_t , the aggregate prices are also characterized (Median also works well).
- > Then, we need to decide the **parametric form** of the law of motion.
- So start from the following parameter guesses $(\alpha_{S}^{K}, \beta_{S}^{K}; \alpha_{S}^{p}, \beta_{S}^{p})$

$$log(K_{t+1}) = \alpha_{S}^{K} + \beta_{S}^{K} log(K_{t}) \text{ when } S_{t} = S$$
$$log(p_{t}) = \alpha_{S}^{p} + \beta_{S}^{p} log(K_{t}) \text{ when } S_{t} = S$$

• K_t does not immediately give p_t (no closed-form). But it should give some inference on p_t !

Computation - GE: Solution

	Model	Computation	Concluding remarks
00	00000000	00000000	00

Value function iteration with accelerator

Now we know p(S), if we are given with K. The pseudo code is as follows:

- 1. Guess $J^{(n)} : \mathcal{K} \times \mathcal{Z} \times \mathcal{A} \times \mathcal{K}^{Agg} \to \mathbb{R}$
- 2. Solve for the policy function, $g_k^{(n)}$ (using monotonicity: $g_k^{(n)} \ge g_{\widetilde{\iota}}^{(n)}$ for $k \ge \widetilde{k}$).
 - We have K, so we know (p, K') from the law of motion.
 - Interpolate the value functions over K' to have $J^{(n)}(\cdot, z'; A', K')$
 - Then, the problem becomes a typical VFI.
- 3. Update $J^{(n+1)}$ using the policy function, $g_k^{(n)}$.
- 4. Update $J^{(n+2)}$ using the policy function, $g_k^{(n)}$.
- 5. Update $J^{(n+m)}$ using the policy function, $g_k^{(n)}$.
- 6. Check if $||J^{(n+m)} J^{(n+m-1)}||_p < Tol$
 - If yes, the solution converged.
 - If no, go back to step 1.

. . .

Computation - GE: Simulation

Non-trivial market clearing condition (Revisited)

We use a non-stochastic iteration method. (Eigenvalue method is not feasible).

- Simulate a long enough aggregate shock path using Γ_S . (Not idiosyncratic shocks)
- Start from an initial guess \mathcal{H}_0 . Compute the corresponding K_0 . And then internal loop.
 - Guess p_0 , and solve the problem to get g_{d0} and g_{l0} .
 - Compute c_0 using $(\mathcal{H}_0, g_{d0}, g_{l0}, w_0)$.
 - Compute $p_0^{update} = 1/c_0$, and repeat the steps until $||p_0 p_0^{update}|| < tol$.
 - So, we have $(K_0, p_0^{converged})$.
- ▶ Let \mathcal{H}_0 evolve to \mathcal{H}_1 using $g_{a0}^{converged}$, and compute the corresponding K_1 .
 - Guess p_1 , and solve the problem to get g_{d1} and g_{l1} .
 - Compute c_1 using $(\mathcal{H}_1, g_{d1}, g_{l1}, w_1)$.
 - Compute $p_1^{update} = 1/c_1$, and repeat the steps until $||p_1 p_1^{update}|| < tol$.
 - So, we have $(K_1, p_1^{converged})$.
- By repeating this process, we obtain $\{K_t, p_t^{converged}\}_{t=0}^T$.
- ▶ Discard the the burn-in period to get $\{K_t, p_t^{converged}\}_{t=burnln}^T$:

▶ ...

Updating the parameters

- We have $\{K_t, p_t^{converged}\}_{t=burnIn}^T$ and $\{S_t\}_{t=burnIn}^T$.
- Fit the time-series into the parametric form of the law of motion to estimate the parameters: (α^K_S, β^K_S; α^p_S, β^p_S)

$$log(K_{t+1}) = \alpha_{S}^{K} + \beta_{S}^{K} log(K_{t}) \text{ when } S_{t} = S$$
$$log(p_{t}^{converged}) = \alpha_{S}^{p} + \beta_{S}^{p} log(K_{t}) \text{ when } S_{t} = S$$

- ▶ If the parameter estimates are not close to the guess, return to the initial step.
- Otherwise, the solution is converged.
- Check R^2 as the first check for the validity of the parametric form.

Close-to-perfect aggregation

Productivity ^a	β_0	β_1	S.E.	Adj. R ²
A. Forecasting m'_1				
z ₁ (119 obs)	0.009	0.800	0.15e-3	1.0000
z ₂ (298 obs)	0.016	0.798	0.22e-3	0.9999
z ₃ (734 obs)	0.023	0.796	0.23e-3	0.9999
z ₄ (1,208 obs)	0.030	0.795	0.26e-3	0.9999
z ₅ (1,682 obs)	0.037	0.794	0.27e-3	0.9999
r ₆ (1,871 obs)	0.044	0.079	0.28e-3	0.9999
z ₇ (1,706 obs)	0.051	0.793	0.26e-3	0.9999
z_8 (1,237 obs)	0.058	0.792	0.24e-3	0.9999
z ₀ (751 obs)	0.065	0.792	0.23e-3	0.9999
z ₁₀ (295 obs)	0.072	0.791	0.25e-3	0.9999
z ₁₁ (99 obs)	0.079	0.791	0.19e-3	0.9999
B. Forecasting p				
r ₁ (119 obs)	0.994	-0.397	0.03e-3	1.0000
z ₂ (298 obs)	0.986	-0.395	0.04e-3	1.0000
z ₃ (734 obs)	0.977	-0.394	0.04e-3	1.0000
z ₄ (1,208 obs)	0.968	-0.393	0.05e-3	1.0000
z ₅ (1,682 obs)	0.958	-0.392	0.05e-3	1.0000
z ₆ (1,871 obs)	0.949	-0.391	0.05e-3	1.0000
z ₇ (1,706 obs)	0.940	-0.389	0.05e-3	1.0000
z_8 (1,237 obs)	0.931	-0.388	0.05e-3	1.0000
z ₉ (751 obs)	0.921	-0.386	0.04e - 3	1.0000
z ₁₀ (295 obs)	0.912	-0.384	0.05e-3	1.0000
z ₁₁ (99 obs)	0.903	-0.382	0.04e-3	1.0000

TABLE A.II FORECASTING RULES IN FULL LUMPY MODEL

^aForecasting rules are conditional on current aggregate total factor productivity z_i . Each regression takes the form $\log(y) = \beta_0 + \beta_1 \log(m_1)$, where $y = m'_1$ or p.

Notes: The table is from Khan and Thomas (2008).

Concluding remarks

Summary

- ▶ Khan and Thomas (2008) provides a great benchmark to start with.
 - The micro-level non-linearity washes out if the general equilibrium effect is strong enough.
 - Strength of the general equilibrium effect depends on the price-elasticities of agents.
 - Are the price-elasticities at an empirically-supported range?
- ▶ The normalization technique is a great idea: See Winberry (2021) and Lee (2022).
- Thanks to the close-to-perfect aggregation, the algorithm of Krusell and Smith (1997) perfectly works.
 - The log-linear law of motion of sufficient statistics perfectly governs the aggregate dynamics.
 - No closed-form for p(S): the internal loop is needed at a computational cost.
- What about financial frictions?
 - Consult with Ferreira, Haber, and Rörig (2021).
 - Real friction vs. Financial friction

Recursive competitive equilibrium: consistency condition Pack

$$\begin{array}{ll} (\text{Consistency}) \quad G_{\Phi}(\Phi) = H(\Phi) = \Phi', \text{ where for } \forall K' \subseteq \mathbb{K} \text{ and } z' \in \mathbb{Z}, \\ \\ \Phi'(K',z') = \int \mathsf{\Gamma}_{z,z'} \Biggl(\mathbb{I}\{g_{k^*}(k,z;S) \in K'\} \frac{g_{\xi^*}(k,z;S)}{\overline{\xi}} \\ \\ + \mathbb{I}\{g_{k^c}(k,z;S) \in K'\} \frac{1 - g_{\xi^*}(k,z;S)}{\overline{\xi}} \Biggr) d\Phi \end{array}$$