Solving Dynamic Games with Newton's Method

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Discrete-Time Finite-State Stochastic Games

Central tool in analysis of strategic interactions among forward-looking players in dynamic environments

Example: The Ericson & Pakes (1995) model of dynamic competition in an oligopolistic industry

Little analytical tractability

Most popular tool in the analysis: The Pakes & McGuire (1994) algorithm to solve numerically for an MPE (and variants thereof)

Applications

Advertising (Doraszelski & Markovich 2007)

Capacity accumulation (Besanko & Doraszelski 2004, Chen 2005, Ryan 2005, Beresteanu & Ellickson 2005)

Collusion (Fershtman & Pakes 2000, 2005, de Roos 2004)

Consumer learning (Ching 2002)

Firm size distribution (Laincz & Rodrigues 2004)

Learning by doing (Benkard 2004, Besanko, Doraszelski, Kryukov & Satterthwaite 2007)

Applications cont'd

Mergers (Berry & Pakes 1993, Gowrisankaran 1999)

Network externalities (Jenkins, Liu, Matzkin & McFadden 2004, Markovich 2004, Markovich & Moenius 2007)

Productivity growth (Laincz 2005)

R&D (Gowrisankaran & Town 1997, Auerswald 2001, Song 2002, Yeltekin et al. 2007)

Technology adoption (Schivardi & Schneider 2005)

International trade (Erdem & Tybout 2003)

Finance (Goettler, Parlour & Rajan 2004, Kadyrzhanova 2005).

Need for better Computational Techniques

Doraszelski and Pakes (2006, in: Handbook of IO)

"Moreover the burden of currently available techniques for computing equilibria to the models we do know how to analyze is still large enough to be a limiting factor in the analysis of many empirical and theoretical issues of interest."

This Tutorial

1. Discrete-Time Finite-State Stochastic Games

2. Separable Game

3. Solution Methods for Dynamic Games

Discrete-Time Finite-Space Stochastic Games

State Space

Infinite-horizon game in discrete time $t = 0, 1, 2, \ldots$

Set of N players, $i = 1, \ldots, N$

At time t player i is in one of finitely many states $x_t^i \in X^i$

State space of the game $X = \prod_i X^i$

State in period t is $x_t = (x_t^1, \ldots, x_t^N)$

Notation: $x_t^{-i} = (x_t^1, \ldots, x_t^{i-1}, x_t^{i+1}, \ldots, x_t^N)$

Player's Actions and Transitions

Player i's action in period t is $u_t^i \in U^i(x_t)$

Set of feasible actions $U^i(x_t)$ is arbitrary, often $U^i = \mathbb{R}_+^K$

Players' actions at time t: $u_t = (u_t^1, \ldots, u_t^N)$

Law of motion: State follows a controlled discrete-time, finite-state, first-order Markov process with transition probability $\Pr(x' | u_t, x_t)$

Special case of independent transitions:

$$\Pr(x' | u_t, x_t) = \prod_{i=1}^{N} \Pr^i\left(\left(x'\right)^i | u_t^i, x_t^i\right)$$

Objective Function

Player i receives a payoff of $\pi^i(u_t, x_t)$ in period t

Objective is to maximize the expected NPV of future cash flows

$$\mathsf{E}\left\{\sum_{t=0}^{\infty} \beta^t \pi^i\left(u_t, x_t\right)\right\},$$

with discount factor $\beta \in (0,1)$

Bellman Equation

$V^i(x)$ is the expected NPV to player i if the current state is x

Bellman equation for player i is

$$V^i(x) = \max_{u^i} \pi^i\left(u^i, U^{-i}(x), x\right) + \beta \mathsf{E}_{x'}\left\{V^i\left(x'\right) | u^i, U^{-i}(x), x\right\} \quad (1)$$

where $U^{-i}(x)$ denotes feedback (Markovian) strategies of other players

Player i's strategy is given by

$$U^i(x) = \arg\max_{u^i} \pi^i\left(u^i, U^{-i}(x), x\right) + \beta \mathsf{E}_{x'}\left\{V^i\left(x'\right) | u^i, U^{-i}(x), x\right\} \quad (2)$$

System of equations defined by (1) and (2) for each player $i = 1, \ldots, N$ and each state $x \in X$ defines a pure-strategy MPE

Example of a Separable Game: Patent Race

Patent Race Between Two Firms

N innovation stages

Firms start race at stage 0

Period t innovation stages: $(x_{1,t}, x_{2,t})$ where
$x_{i,t} \in X \equiv \{0, ..., N\}, i = 1, 2$

Period t investment: $a_{i,t} \in A = [0, \bar{A}] \subset \mathbb{R}_+$, $i = 1, 2$

Cost of investment: $C_i(a) = c_i a^\eta,\ \eta \in \mathbb{N},\ c_i > 0,\ i = 1, 2$

Independent and stochastic innovation technologies

Transition from State to State

Transition from period to period: $x_{i,t+1} = x_{i,t}$ or $x_{i,t+1} = x_{i,t} + 1$

Markov process (depends on investment levels)

Firm i's state evolves according to

$$x_{i,t+1} = \begin{cases} x_{i,t}, & \text{with probability } \; p(x_{i,t}|a_{i,t}, x_{i,t}) \\ x_{i,t} + 1, & \text{with probability } \; p(x_{i,t} + 1|a_{i,t}, x_{i,t}) \end{cases}$$

Distribution over next period's states

$$\begin{aligned} p(x|a, x) &= F(x|x)^a \\ p(x + 1|a, x) &= 1 - F(x|x)^a \end{aligned}$$

$F(x|x) \in (0, 1)$ is probability that there is no change in state if $a = 1$

Firms' Optimization Problem

First firm to reach state N wins the race and receives prize Ω

Ties are broken by flip of a coin

Firms discount future costs and revenues at common rate $\beta < 1$

Firms' objective: maximize expected discounted payoffs

Equilibrium I

Restriction to pure Markov strategies

Firm i's strategy: $\sigma_i(\cdot) : X \times X \to A$

Expected discounted payoff: $V_i(\cdot) : X \times X \to \mathbb{R}$

Bellmann equation for $x_i, x_{-i} < N$,

$$V_i(x_i, x_{-i}) =$$

$$\max_{a_i \in A} \left\{ -C_i(a_i) + \beta \sum_{x'_i, x'_{-i}} p(x'_i | a_i, x_i) p(x'_{-i} | a_{-i}, x_{-i}) V_i(x'_i, x'_{-i}) \right\}$$

Equilibrium II

Boundary condition at terminal states

$$V_i(x_i, x_{-i}) = \begin{cases} \Omega, & \text{for } x_{-i} < x_i = N \\ \Omega/2, & \text{for } x_i = x_{-i} = N \\ 0, & \text{for } x_i < x_{-i} = N \end{cases}$$

Optimal strategies satisfy

$$\sigma_i(x_i, x_{-i}) =$$

$$\arg\max_{a_i \in A} \left\{ -C_i(a_i) + \beta \sum_{x_i', x_{-i}'} p(x_i'|a_i, x_i) p(x_{-i}'|a_{-i}, x_{-i}) V_i(x_i', x_{-i}') \right\}$$

Our Equilibrium Equations

$$
\begin{aligned}
0 &= -V_i(x_i, x_{-i}) - c_i a_i^{\eta} + \beta \sum_{x_i', x_{-i}'} p(x_i' | a_i, x_i) p(x_{-i}' | a_{-i}, x_{-i}) V_i(x_i', x_{-i}') \\
0 &= -\eta c_i a_i^{\eta - 1} + \beta \sum_{x_i', x_{-i}'} \frac{\partial}{\partial a_i} p(x_i' | a_i, x_i) p(x_{-i}' | a_{-i}, x_{-i}) V_i(x_i', x_{-i}')
\end{aligned}
$$

Parameter specification: c_1, c_2, η, $F(x_1, x_2) \equiv F$, Ω

Unknowns: $V_1(x_1, x_2)$, $V_2(x_1, x_2)$, $a_1(x_1, x_2)$, $a_2(x_1, x_2)$

Four equations per stage (x_i, x_{-i})

Backward induction: instead of solving all equations simultaneously

solve each stage game separately

Solving Systems of Nonlinear Equations

Nonlinear Systems of Equations

System $F(x) = 0$ of n nonlinear equations in n variables $x = (x_1, x_2, \ldots, x_n) \in \mathbb{R}^n$

$$\begin{array}{rcl} F_1(x_1, x_2, \ldots, x_n) & = & 0 \\ F_2(x_1, x_2, \ldots, x_n) & = & 0 \\ & \vdots & \\ F_{n-1}(x_1, x_2, \ldots, x_n) & = & 0 \\ F_n(x_1, x_2, \ldots, x_n) & = & 0 \end{array}$$

Initial guess $x^0 = (x_1^0, x_2^0, \ldots, x_n^0)$

Methods generate a sequence of iterates $x^0, x^1, x^2, \ldots, x^k, x^{k+1}, \ldots$

Solution Methods

Most popular methods in economics for solving $F(x) = 0$

1. Gauss-Jacobi Method
2. Gauss-Seidel Method
3. Newton's Method
4. Homotopy Methods

Gauss-Jacobi Method

Last iterate $x^k = (x_1^k, x_2^k, x_3^k, \ldots, x_{n-1}^k, x_n^k)$

New iterate x^{k+1} computed by repeatedly solving one equation in one variable using only values from x^k

$$\begin{aligned}
F_1(x_1^{k+1}, x_2^k, x_3^k, \ldots, x_{n-1}^k, x_n^k) &= 0 \\
F_2(x_1^k, x_2^{k+1}, x_3^k, \ldots, x_{n-1}^k, x_n^k) &= 0 \\
&\vdots \\
F_{n-1}(x_1^k, x_2^k, \ldots, x_{n-2}^k, x_{n-1}^{k+1}, x_n^k) &= 0 \\
F_n(x_1^k, x_2^k, \ldots, x_{n-2}^k, x_{n-1}^k, x_n^{k+1}) &= 0
\end{aligned}$$

Computer storage: Need to store both x^k and x^{k+1}

Interpretation as iterated simultaneous best reply

Gauss-Seidel Method

Last iterate $x^k = (x_1^k, x_2^k, x_3^k, \ldots, x_{n-1}^k, x_n^k)$

New iterate x^{k+1} computed by repeatedly solving one equation in one variable and immediately updating the iterate

$$\begin{aligned}
F_1(x_1^{k+1}, x_2^k, x_3^k, \ldots, x_{n-1}^k, x_n^k) &= 0 \\
F_2(x_1^{k+1}, x_2^{k+1}, x_3^k, \ldots, x_{n-1}^k, x_n^k) &= 0 \\
&\vdots \\
F_{n-1}(x_1^{k+1}, x_2^{k+1}, \ldots, x_{n-2}^{k+1}, x_{n-1}^{k+1}, x_n^k) &= 0 \\
F_n(x_1^{k+1}, x_2^{k+1}, \ldots, x_{n-2}^{k+1}, x_{n-1}^{k+1}, x_n^{k+1}) &= 0
\end{aligned}$$

Computer storage: Need to store only one vector

Interpretation as iterated sequential best reply

Solving a Simple Cournot Game

N firms

Firm i's production quantity q_i

Total output is $Q = q_1 + q_2 + \ldots + q_N$

Linear inverse demand function, $P\left(Q\right) = A - Q$

All firms have identical cost functions $C(q) = \frac{2}{3} c q^{3/2}$

Firm i's profit function Π_i is

$$\Pi_i = q_i P\left(q_i + Q_{-i}\right) - C(q_i) = q_i \left(A - \left(q_i + Q_{-i}\right)\right) - \frac{2}{3} c q_i^{3/2}$$

First-order Conditions

Necessary and sufficient first-order conditions

$$A - Q_{-i} - 2q_i - c\sqrt{q_i} = 0$$

Firm i's best reply $R(Q_{-i})$ to a production quantity Q_{-i} of its competitors

$$q_i = R(Q_{-i}) = \left(\frac{A - Q_i}{2} + \frac{c^2}{8}\right) - \frac{c}{2}\sqrt{\frac{A - Q_{-i}}{2} + \frac{c^2}{16}}$$

Parameter values: $N = 2$ firms, $A = 145$, $c = 4$

Solving the Cournot Game with Gauss-Jacobi

k	q_i^k	$\max_i \lvert q_i^k - q_i^{k-1} \rvert$
0	10	–
1	52.9471	42.9471
2	34.3113	18.6358
3	42.3318	8.02047
4	38.8656	3.46613
5	40.3611	1.49545
6	39.7154	0.645682
7	39.9941	0.278695
15	39.9102	0.000336014
16	39.9100	0.000145047
20	39.910075	5.036 (−6)
21	39.910078	2.174 (−6)

Solving the Cournot Game with Gauss-Seidel

k	q_1^k	q_2^k	$\max_i \lvert q_i^k - q_i^{k-1} \rvert$
0	10	10	–
1	52.9471	34.3113	42.9471
2	42.3318	38.8656	10.6153
3	40.3611	39.7154	1.97068
4	39.9941	39.8738	0.366987
5	39.9257	39.9033	0.0683762
6	39.913	39.9088	0.0127409
7	39.9106	39.9098	0.00237412
8	39.9102	39.91	0.000442391
9	39.9101	39.9101	0.0000824347
10	39.9101	39.9101	0.0000153608
11	39.91008	39.91008	2.862 (−6)

Gauss-Jacobi with $N = 4$ firms blows up

Cournot equilibrium $q^i = 25$ for all firms
$x^0 = (24, 25, 25, 25)$

k	q_1^k	$q_2^k = q_3^k = q_4^k$	$\max_i \|q_i^k - q_i^{k-1}\|$
1	25	25.4170	1
2	24.4793	24.6527	0.7642
3	25.4344	25.5068	0.9551
4	24.3672	24.3973	1.1095
5	25.7543	25.7669	1.3871
13	29.5606	29.5606	8.1836
14	19.3593	19.3593	10.201
15	32.1252	32.1252	12.766
20	4.8197	4.8197	37.373
21	50.9891	50.9891	46.169

Newton's Method

Foundation of Newton's Method: Taylor's Theorem

THEOREM. Suppose the function $F : X \to \mathbb{R}^m$ is continuously differentiable on the open set $X \subset \mathbb{R}^n$ and that the Jacobian function J_F is Lipschitz continuous at x with Lipschitz constant $\gamma^l(x)$. Also suppose that for $s \in \mathbb{R}^n$ the line segment $x + \theta s \in X$ for all $\theta \in [0, 1]$. Then, the linear function $L(s) = F(x) + J_F(x)s$ satisfies

$$\|F(x+s) - L(s)\| \leq \frac{1}{2}\gamma^L(x)\|s\|^2 \ .$$

Taylor's Theorem suggests the approximation
$F(x+s) \approx L(s) = F(x) + J_F(x)s$

Newton's Method in Pure Form

Initial guess x^0

Given iterate x^k choose Newton step by calculating a solution s^k to the system of linear equations

$$J_F(x^k)\ s^k = -F(x^k)$$

New iterate $x^{k+1} = x^k + s^k$

Excellent local convergence properties

Solving Cournot Game ($N = 4$) with Newton's Method

k	q_i^k	$\max_i \lvert q_i^k - q_i^{k-1} \rvert$
0	10	–
1	24.6208	14.6208
2	24.9999	0.3791
3	25.0000	0.000108
4	25.0000	8.67(−12)

Shortcomings of Newton's Method

If initial guess x^0 is far from a solution Newton's method may behave erratically; for example, it may diverge or cycle (!)

If $J_F(x^k)$ is singular the Newton step may not be defined

It may be too expensive to compute the Newton step s^k for large systems of equations

The root x^* may be degenerate ($J_F(x^*)$ is singular) and convergence is very slow

Practical variants of Newton-like methods overcome all these issues

Practical Newton-like Method

General idea: Obtain global (!) convergence by combining the Newton step with line-search or trust-region methods from optimization

Merit function monitors progress towards root of F

Most widely used merit function is sum of squares

$$M(x) = \frac{1}{2}\|F(x)\|^2 = \frac{1}{2}\sum_{i=1}^{n} F_i^2(x)$$

Any root x^* of F yields global minimum of M

Local minimizers with $M(x) > 0$ are not roots of F

$$\nabla M(\tilde{x}) = J_F(\tilde{x})^\top F(\tilde{x}) = 0$$

and so $F(\tilde{x}) \neq 0$ implies $J_F(\tilde{x})$ is singular

Line Search Method

Newton step

$$J_f(x^k)\ s^k = -F(x^k)$$

yields a descent direction of M as long as $F(x^k) \neq 0$

$$\left(s^k\right)^\top \nabla M(x^k) = \left(s^k\right)^\top J_F(x^k)^\top F(x^k) = -\|F(x^k)\|^2 < 0$$

Given step length α^k the new iterate is

$$x^{k+1} = x^k + \alpha^k s^k$$

Step length

Inexact line search condition (Armijo condition)

$$M(x^k + \alpha s^k) \leq M(x^k) + c\ \alpha\ \left(\nabla M(x^k)\right)^\top s^k$$

for some constant $c \in (0, 1)$

Step length is the largest α satisfying the inequality

For example, try $\alpha = 1, \frac{1}{2}, \frac{1}{2^2}, \frac{1}{2^3}, \ldots$

This approach is not Newton's method for minimization

No computation or storage of Hessian matrix

Global Convergence Property

THEOREM. Suppose that J_F is Lipschitz continuous and both $\|J_F(x)\|$ and $\|F(x)\|$ are bounded above in an open neighborhood of the level set $\left\{x : M(x) \leq M(x^0)\right\}$. Under some further mild technical conditions the sequence of iterates $x^0, x^1, \ldots, x^k, x^{k+1}, \ldots$ satisfies

$$\left(J_F(x^k)\right)^\top F(x^k) \to 0$$

as $k \to \infty$.
Moreover, if $\|J_F(x^k)\| \geq \delta > 0$ then

$$F(x^k) \to 0.$$

Cournot Game with Learning and Investment

$N = 2$ firms in dynamic Cournot competition

State of the game: production cost of two firms

Each period: Firms engage is quantity competition

Stochastic transition to state in next period depends on three forces

Learning: Current output may lead to lower production cost

Investment: Firms can also make investment expenditures to reduce cost

Depreciation: Shock to efficiency may increase cost

Period Game

Firm i's production quantity q_i

Total output is $Q = q_1 + q_2$

Linear inverse demand function, $P(Q) = A - Q$

Firms' production cost functions are quadratic $CP_i(q) = \frac{1}{2} b_i q^2$

Firms' profit functions are

$$\begin{aligned} \Pi_1 &= q_1 \; P(q_1 + q_2) - \theta_1 \left(\frac{1}{2} b_1 q_1^2 \right) \\ \Pi_2 &= q_2 \; P(q_1 + q_2) - \theta_2 \left(\frac{1}{2} b_2 q_2^2 \right) \end{aligned}$$

Efficiency of firm i is given by θ_i

Dynamic Setting

Each firm can be in one of S states, $j = 1, 2, \ldots, S$

State j of firm i determines its efficiency level
$\theta_i = \Theta^{(j-1)/(S-1)}$ for some $\Theta \in (0, 1)$

Total range of efficiency levels $[\Theta, 1]$ for any S

Possible transitions from state j to states $j-1,\ j,\ j+1$ in next period

Transition probabilities for firm i depend on
production quantity q_i
investment effort u_i
depreciation shock

Transition Probabilities

Probability of successful learning (j to $j+1$), $\psi(q) = \frac{\kappa q}{1+\kappa q}$

Probability of successful investment (j to $j+1$), $\phi(u) = \frac{\alpha u}{1+\alpha u}$

Cost of investment for firm i, $CI_i(u) = \frac{1}{S-1}\left(\frac{1}{2} d_i u^2\right)$

Probability of depreciation shock, δ

These individual probabilities,appropriately combined, yield transition probabilities

Equilibrium Equations

Bellman equation for each firm

First-order condition w.r.t. quantity q_i

First-order condition w.r.t. investment u_i

Three equations per firm per state

Total of $6\ S^2$ equations

GAMS Code I

```
V1(m1e,m2e) =e= Q1(m1e,m2e)*(1 - Q1(m1e,m2e)/M -
Q2(m1e,m2e)/M) -  ((b1*power(Q1(m1e,m2e),2))/2. +
a1*Q1(m1e,m2e))*theta1(m1e) -  ((d1*power(U1(m1e,m2e),2))/2. +
c1*U1(m1e,m2e))/(-1 + Nst) + (beta*((1 -  2*delta + power(delta,2)
+ Q2(m1e,m2e)*(delta*kappa - kappa*power(delta,2) +
alpha*kappa*power(delta,2)*U1(m1e,m2e)) + (alpha*delta -
alpha*power(delta,2))*U2(m1e,m2e) + Q1(m1e,m2e)*(delta*kappa -
kappa*power(delta,2) + power(delta,2)*power(kappa,2)*Q2(m1e,m2e)
+  alpha*kappa*power(delta,2)*U2(m1e,m2e)) +
U1(m1e,m2e)*(alpha*delta -  alpha*power(delta,2) +
```

GAMS Code II

```
power(alpha,2)*power(delta,2)*U2(m1e,m2e)))*V1(m1e,m2e) + (delta -
power(delta,2) + kappa*power(delta,2)*Q1(m1e,m2e) +
alpha*power(delta,2)*U1(m1e,m2e))*V1(m1e,m2e - 1) + ((alpha -
2*alpha*delta + alpha*power(delta,2))*U2(m1e,m2e) +
(delta*power(alpha,2) -
power(alpha,2)*power(delta,2))*U1(m1e,m2e)*U2(m1e,m2e) +
Q2(m1e,m2e)*(kappa - 2*delta*kappa + kappa*power(delta,2) +
(alpha*kappa - alpha*delta*kappa)*U2(m1e,m2e) +
U1(m1e,m2e)*(alpha*delta*kappa - alpha*kappa*power(delta,2) +
delta*kappa*power(alpha,2)*U2(m1e,m2e))) +
Q1(m1e,m2e)*((alpha*delta*kappa -
```

GAMS Code III

```
alpha*kappa*power(delta,2))*U2(m1e,m2e) +
Q2(m1e,m2e)*(delta*power(kappa,2) - power(delta,2)*power(kappa,2)
+  alpha*delta*power(kappa,2)*U2(m1e,m2e))))*V1(m1e,m2e + 1) +
(delta -  power(delta,2) + kappa*power(delta,2)*Q2(m1e,m2e) +
alpha*power(delta,2)*U2(m1e,m2e))*V1(m1e - 1,m2e) +
power(delta,2)*V1(m1e -  1,m2e - 1) + ((alpha*delta -
alpha*power(delta,2))*U2(m1e,m2e) +  Q2(m1e,m2e)*(delta*kappa -
kappa*power(delta,2) +  alpha*delta*kappa*U2(m1e,m2e)))*V1(m1e -
1,m2e + 1) + ((alpha*delta*kappa -
alpha*kappa*power(delta,2))*Q2(m1e,m2e)*U1(m1e,m2e) +
U1(m1e,m2e)*(alpha -  2*alpha*delta + alpha*power(delta,2) +
(delta*power(alpha,2) -
```

GAMS Code IV

```
power(alpha,2)*power(delta,2))*U2(m1e,m2e)) + Q1(m1e,m2e)*(kappa
- 2*delta*kappa + kappa*power(delta,2) +
Q2(m1e,m2e)*(delta*power(kappa,2) - power(delta,2)*power(kappa,2)
+ alpha*delta*power(kappa,2)*U1(m1e,m2e)) + (alpha*delta*kappa -
alpha*kappa*power(delta,2))*U2(m1e,m2e) +
U1(m1e,m2e)*(alpha*kappa - alpha*delta*kappa +
delta*kappa*power(alpha,2)*U2(m1e,m2e))))*V1(m1e + 1,m2e) +
((alpha*delta - alpha*power(delta,2))*U1(m1e,m2e) +
Q1(m1e,m2e)*(delta*kappa - kappa*power(delta,2) +
alpha*delta*kappa*U1(m1e,m2e)))*V1(m1e + 1,m2e - 1) +
((power(alpha,2) - 2*delta*power(alpha,2) +
power(alpha,2)*power(delta,2))*U1(m1e,m2e)*U2(m1e,m2e) +
```

GAMS Code V

```
Q2(m1e,m2e)*U1(m1e,m2e)*(alpha*kappa - 2*alpha*delta*kappa +
alpha*kappa*power(delta,2) + (kappa*power(alpha,2) -
delta*kappa*power(alpha,2))*U2(m1e,m2e)) +
Q1(m1e,m2e)*((alpha*kappa - 2*alpha*delta*kappa +
alpha*kappa*power(delta,2))*U2(m1e,m2e) + (kappa*power(alpha,2) -
delta*kappa*power(alpha,2))*U1(m1e,m2e)*U2(m1e,m2e) +
Q2(m1e,m2e)*(power(kappa,2) - 2*delta*power(kappa,2) +
power(delta,2)*power(kappa,2) + (alpha*power(kappa,2) -
alpha*delta*power(kappa,2))*U2(m1e,m2e) +
U1(m1e,m2e)*(alpha*power(kappa,2) - alpha*delta*power(kappa,2) +
power(alpha,2)*power(kappa,2)*U2(m1e,m2e)))))*V1(m1e + 1,m2e +
1)))/((1 + kappa*Q1(m1e,m2e))*(1 + kappa*Q2(m1e,m2e))*(1 +
alpha*U1(m1e,m2e))*(1 + alpha*U2(m1e,m2e)));
```

And that was just one of 6 equations

Results

S	Var	rows	non-zero	dense(%)	Steps	RT (m:s)
20	2400	2568	31536	0.48	5	0 : 03
50	15000	15408	195816	0.08	5	0 : 19
100	60000	60808	781616	0.02	5	1 : 16
200	240000	241608	3123216	0.01	5	5 : 12

Convergence for $S = 200$

Iteration	Residual
0	$1.56(+4)$
1	$1.06(+1)$
2	1.34
3	$2.04(-2)$
4	$1.74(-5)$
5	$2.97(-11)$

Extensions

Complementarity problems

Continuous time setting