DEMOGRAPHIC PRISONNER DILEMMA AS A MEAN FIELD GAMES

René Carmona

Department of Operations Research & Financial Engineering Program in Applied & Computational Mathematics Princeton University

INRIA Short Talk 3/30/17

▲ロ▶ ▲□▶ ▲□▶ ▲□▶ □ のQ@

TURNING A TWO-PLAYER ONE-PERIOD FINITE GAME INTO AN N-PLAYER GAME

- Start with your favorite Two-Players, One Period, Finite States
 - Prisonner Dilemma (or Rock-Paper-Scissor, or)
 - Payoff

$$F(\alpha, \alpha') = \mathbf{1}_{\alpha = \mathcal{C}} (R\mathbf{1}_{\alpha' = \mathcal{C}} - S\mathbf{1}_{\alpha' = \mathcal{D}}) + \mathbf{1}_{\alpha = \mathcal{D}} (T\mathbf{1}_{\alpha' = \mathcal{C}} - P\mathbf{1}_{\alpha' = \mathcal{D}})$$

with T > R > 0 > -S > -P

- N-player Game
 - ► Fix an integer N ≥ 2
 - A family $(\mathbf{N}_{(i,j)})_{(i,j) \in \mathcal{I}^*}$ of independent Poisson processes $\mathbf{N}_{(i,j)} = (N_{(i,j)}(t))_{t \ge 0}$ with rates 1/[N(N-1)].

Dynamics

- ▶ If one of the Poisson processes, say **N**(*i*,*j*) jumps at time *t*,
- we let players i and j play an instance of the one stage game.
- If they use strategies α_t^i and α_t^j , their wealths Y_t^i and Y_t^j are updated:

$$Y_t^i = Y_{t-}^i + F(\alpha_t^i, \alpha^j),$$
 and $Y_t^j = Y_{t-}^j + F(\alpha_t^j, \alpha^j).$

(ロ) (同) (三) (三) (三) (○) (○)

EVOLUTIONARY GAMES

Axelrod (1984), Frank (1993,1994)

- N agents do not consciously optimize over strategic alternatives.
- they inherit a fixed strategy (a phenotype) at birth
- individuals are "hard-wired" to execute a fixed strategy
- they repeat this inherited strategy over and over and over and over
- For the Prisonner Dilemma game individuals are "hard-wired" to execute a fixed strategy C or D
- Assume that the proportion of players wired with C is p
- Assume the players match at random, and when they do, they play a round of Prisonner Dilemma gate.
- In such a game their expected payoffs are given by:

$$\mathbb{E}[C] = pR - (1-p)S$$
 and $\mathbb{E}[D] = pT - (1-p)P$

(ロ) (同) (三) (三) (三) (○) (○)

DEMOGRAPHIC VERSION

J. Epstein

- Still hard-wired individuals of types C and D
- Epstein added a spatial component
 - *m* integer, $\mathbb{T}_m^2 = (\mathbb{Z}/m\mathbb{Z})^2$
 - For $i = 1, \dots, N$, $(\mathbf{X}^i = (X_t^i)_{t \ge 0}$ i.i.d. standard random walks on \mathbb{T}^2
 - Players i and j are allowed to play at time t if
 - ► $N_{i,j}(t)$ jumps

•
$$Y_t^i > 0$$
 and $Y_t^j > 0$

$$\blacktriangleright X_t^i = X_t^j$$

- The state of player *i* evolves as (Xⁱ_t, Yⁱ_t, Zⁱ) where Zⁱ = C or Zⁱ = D does not change with time.
- Showed in Monte Carlo simulations zones of cooperation occur
- The Demographic Prisonner Dilemma game is not really a (dynamic) game since the control / strategy Zⁱ does not change with time !

(日) (日) (日) (日) (日) (日) (日)

DYNAMIC GAME VERSION OF DPD

- Allow players to change type (C or D) dynamically as a function of Yⁱ_t
 - ▶ Player *i* changes his/her status (control) dynamically $(\phi_t^i(Y_t^i) = \mathbf{C} \text{ or } \mathbf{D})$
- Speed up the spacial walks $X_t^i \mapsto X_{\lambda t}^i$ for $\lambda \nearrow \infty$
- Homogenization (Gibaud) using T. Kurtz limit theorems for Markov processes
 - For each feedback (Markovian) φ = (φ¹, · · · , φ^N), Y = (Y^{λ,1}, · · · , Y^{λ,N}) with with Y^{λ,i} = (Y^{λ,i}_t)_{t>0} wealth of player *i* converges as λ ≯ ∞
 - Essentially, homogenization in limit $\lambda \nearrow \infty$ brings the physical positions $(X_t^{\lambda,1}, \cdots, X_t^{\lambda,N})$ to be picked according to their invariant measure

(日) (日) (日) (日) (日) (日) (日)

DYNAMICS OF THE DEMOGRAPHIC GAME

- ▶ If one of the Poisson processes, say $N_{(i,j)}$ jumps at time *t*,
- one checks that the players *i* and *j* are still in the game,
- that their physical states X_t^i and X_t^j are neighbors,
- if so, they play an instance of the one stage game.
- ► If they use strategies α^j_t and α^j_t, their respective wealths are updated in the following way:

$$Y_t^i = Y_{t-}^i + F(\alpha_t^i, \alpha^j),$$
 and $Y_t^j = Y_{t-}^j + F(\alpha_t^j, \alpha^i).$

(日) (日) (日) (日) (日) (日) (日)

CREDITS & STARTING POINT

- Repeated Prisonner Dilemma Game exhibits same repeated one stage Nash equilibrium
- Infinite horizon, depending upon discount factor, zones of cooperation occur

J. Epstein

- Added a spatial component
- Showed in Monte Carlo simulations zones of cooperation occur

Gibaud revisited Epstein's DPD model

- proved
 - homogenization of the spatial component (T. Kurtz limit theorems for Markov processes)

◆□▶ ◆□▶ ▲□▶ ▲□▶ □ のQ@

propagation of chaos of the homogenized model (A.S. Sznitmann)

DYNAMIC DPD AS AN N-PLAYER GAME WITH MEAN FIELD INTERACTIONS

$$Y_{t} = Y_{0} + \int_{[0,t]} \sum_{(i,j) \in \mathcal{I}^{*}} \varphi_{(i,j)}(Y_{s-}, \phi(Y_{s-})N_{(i,j)}(ds))$$

with $\varphi_{(i,j)} = (\varphi_{(i,j)}^1, \cdots, \varphi_{(i,j)}^N)$ are \mathbb{R}^N -valued

- If k fixed, $\varphi_{(i,j)}^k = 0$ unless k = i or k = j
- ▶ **Goal**: rewrite the dynamics of Y_t^k to emphasize the role of Y_t^j with $j \neq k$

Fix k & rewrite the Poisson measures N_{ik} and N_{kj} as:

$$N_{ik}(dt) = \int_{[0,1]} \mathbf{1}_{[\frac{\sigma_t(i)-1}{N-1} < w \le \frac{\sigma_t(i)}{N-1}]} \tilde{N}^1(dt, dw)$$

and

$$N_{kj}(dt) = \int_{[0,1]} \mathbf{1}_{[\frac{\sigma_t(j)-1}{N-1} < w \le \frac{\sigma_t(j)}{N-1}]} \tilde{N}^2(dt, dw)$$

where

- \tilde{N}^1 and \tilde{N}^2 are independent Poisson random measures on $[0,\infty) \times [0,1]$ with intensity $\frac{1}{2}Leb_2$
- $(\sigma_t)_{t\geq 0}$ is a predictable process with values in the set of one-to-one maps from $\{1, \cdots, N\} \setminus \{k\}$ onto $\{1, \cdots, N-1\}$ which we shall specify later on.

MASSAGE THE FORMULA

We have:

$$Y_{t}^{k} = Y_{0}^{k} + \sum_{i=1, i \neq k}^{N} \int_{[0,t] \times [0,1]} \varphi_{ik}^{k}(Y_{s-}, \phi(Y_{s-})) \mathbf{1}_{\left[\frac{\sigma_{s}(i)-1}{N-1} < w \le \frac{\sigma_{s}(i)}{N-1}\right]} \tilde{N}^{1}(ds, dw)$$

+
$$\sum_{j=1, j \neq k}^{N} \int_{[0,t] \times [0,1]} \varphi_{kj}^{k}(Y_{s-}, \phi(Y_{s-})) \mathbf{1}_{\left[\frac{\sigma_{s}(i)-1}{N-1} < w \le \frac{\sigma_{s}(i)}{N-1}\right]} \tilde{N}^{2}(ds, dw)$$
(1)
=
$$Y_{0}^{k} + \int_{[0,t] \times [0,1]} \left(\sum_{i=1, i \neq k}^{N} \varphi_{ik}^{k}(Y_{s-}, \phi(Y_{s-})) \mathbf{1}_{\left[\frac{\sigma_{s}(i)-1}{N-1} < w \le \frac{\sigma_{s}(i)}{N-1}\right]}\right) \tilde{N}(ds, dw)$$

where $\tilde{N}(ds, dw) = \tilde{N}^1(ds, dw) + \tilde{N}^2(ds, dw)$ is Poisson random measure on $[0, \infty) \times [0, 1]$ with intensity *Leb*₂.

SEARCH FOR BEST RESPONSE OF PLAYER k

Assume all players $j \neq k$ use same strategy $\tilde{\phi}^k,$ and find best response ϕ^k by player k

$$Y_{t}^{k} = Y_{0}^{k} + \int_{[0,t]\times[0,1]} \mathbf{1}_{Y_{s-}^{k}>0} \sum_{i=1, i\neq k}^{N} \mathbf{1}_{Y_{s-}^{i}>0} F(\phi^{k}(Y_{s-}^{k}), \tilde{\phi}^{k}(Y_{s-}^{i})) \\ \mathbf{1}_{[\frac{\sigma_{s}(i)-1}{N-1} < w \le \frac{\sigma_{s}(i)}{N-1}]} \tilde{N}(ds, dw)$$

CHOOSE THE PREDICTABLE $\sigma_t(i)$ **Appropriately**

• Order the wealths
$$Y_t^{(1),-k} \leq Y_t^{(2),-k} \leq \cdots \leq Y_t^{(N-1),-k}$$

• Choose $\sigma_t : \{1, \cdots, N\} \setminus \{k\} \mapsto \{1, \cdots, N-1\}$ so that

$$Y_t^{(i),-k} = Y_t^{\sigma_t^{-1}(i)}, \qquad i = 1, \cdots, N-1.$$

► Denote by $\tilde{\mu}_t^{-k}$ tje empirical measure $\tilde{\mu}_t^{-k} = \frac{1}{N-1} \sum_{i=1, i \neq k}^N \delta_{Y_t^i}$

► Denote $[0,1] \ni w \mapsto \tilde{Q}_t^{-k}(w) \in [0,\infty)$ its quantile function

From

$$Y_{t}^{k} = Y_{0}^{k} + \int_{[0,t] \times [0,1]} \mathbf{1}_{Y_{s-}^{k} > 0} \Big(\sum_{i=1}^{N-1} \mathbf{1}_{Y_{s-}^{(i),-k} > 0} F(\phi^{k}(Y_{s-}^{k}, \tilde{\phi}^{k}(Y_{s-}^{(i),-k})) \ \mathbf{1}_{[\frac{i-1}{N-1} < w \le \frac{i}{N-1}]} \Big) \tilde{N}(ds, dw)$$

and

$$\frac{i-1}{N-1} < w \le \frac{i}{N-1} \iff \tilde{Q}_t^{-k}(w) = Y_t^{(i),-k}, \qquad t \ge 0$$

we get

$$Y_{t}^{k} = Y_{0}^{k} + \int_{[0,t] \times [0,1]} F\left(Y_{s-}^{k}, \tilde{Q}_{s-}^{-k}(w), \phi^{k}(Y_{s-}^{k}), \tilde{\phi}^{k}(\tilde{Q}_{s-}^{-k}(w))\right) \tilde{N}(ds, dw)$$

▲□▶ ▲□▶ ▲ 三▶ ▲ 三▶ - 三 - のへぐ

MEAN FIELD GAME PROBLEM

◊ Best Response Step:

- ▶ Fix a distributed feedback function $\tilde{\phi} : [0, \infty) \times [0, \infty) \ni (t, y) \mapsto \tilde{\phi}_t(y) \in A$
- Fix a flow (µ̃_t)_{t≥0} of probability measures
- Solve:

,

$$\sup_{\phi} \mathbb{E} \Big[g(Y_T, \tilde{\mu}_T) + \int_0^T f(t, Y_t, \phi_t, \tilde{\phi}_t, \tilde{\mu}_t) dt \Big]$$
(2)

under the dynamic constraint:

$$Y_{t} = Y_{0} + \int_{[0,t]\times[0,1]} F\Big(Y_{s-}, \tilde{Q}_{s-}(w), \phi(Y_{s-}), \tilde{\phi}(\tilde{Q}_{s-}(w)))\Big) \tilde{N}(ds, dw)$$
(3)

where \tilde{Q}_t denotes the quantile function of the probability measure $\tilde{\mu}_t$.

 \diamond *Fixed Point Step:* If $(\hat{\phi}, \hat{\mathbf{Y}} = (\hat{Y}_t)_{t \ge 0})$ solves the above problem, demand:

$$\tilde{\phi} = \hat{\phi}, \quad \text{and} \quad \tilde{\mu}_t = \mathcal{L}(\hat{Y}_t), \text{ for } 0 \le t \le T.$$
 (4)

Example with Wealth in $\{0, 1, \cdots, 100\}$, $\mu_0 = \delta_{50}$



FIGURE: Time evolution of the total mass of the distribution μ_t . Killing has no effect.

▲□ > ▲圖 > ▲目 > ▲目 > ▲目 > ● ④ < @

Example with Wealth in $\{0, 1, \dots, 50\}$



FIGURE: Left: Time evolution of total mass (killing if $Y_t < 0$ or $Y_t > 50$. Right: Time evolution of the distribution $\mu_t(y)$ for $y = 0, 1, \dots, 50$.

◆□> ◆□> ◆豆> ◆豆> ・豆 ・ 釣べ⊙