

# Mean-Field Games with non-convex Hamiltonian

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# Plan

- Risk-sensitive and robust control
- Robust MFGs
- Uniqueness of the solutions: the classical conditions and the "small data" regime
- Examples of non-uniqueness [M.B. and M. Fischer]
- Well-posedness with Neumann B.C. and non-convex  $H$  [M.B. and M. Cirant]
- MFGs with several populations [Achdou - M.B.- Cirant]
- Remarks and perspectives

# Risk-sensitive control

Consider a stochastic control system

$$dX_s = f(X_s, \alpha_s) ds + \sigma(X_s) dW_s, \quad X_t = x \in \mathbf{R}^d, \quad 0 \leq t \leq T$$

with  $W_s$  a Brownian motion,  $\alpha_s = \text{control}$  (adapted to  $W_s$ ),  
 $\sigma$  a **volatility** matrix, and a finite horizon loss functional

$$C_T(t, x, \alpha.) := \int_t^T L(X_s, \alpha_s) ds + G(X_T).$$

The usual cost functional is  $J_T(t, x, \alpha.) := E[C_T(t, x, \alpha.)]$ .

The **Risk-sensitive** cost functional is

$$I_T(t, x, \alpha.) := \delta \log E \left[ e^{\frac{1}{\delta} C_T(t, x, \alpha.)} \right]$$

$\delta > 0 = \text{risk sensitivity index}$  (small  $\delta = \text{great sensitivity}$ ).

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Note:

$$I_T = E[C_T] + \frac{1}{2\delta} \text{Var}(C_T) + O\left(\frac{1}{\delta}\right) \quad \text{as } \delta \rightarrow \infty,$$

and in general  $I_T$  takes into account all moments of the cost  $C_T$ , not only  $E$ .

# The risk-sensitive H-J equation

The risk-sensitive value function is  $v(x) := \inf_{\alpha} I_T(t, x, \alpha)$ .

From the Hamilton-Jacobi-Bellman equation for  $\inf_{\alpha} E \left[ e^{\frac{1}{\delta} C_T} \right]$  easy calculations give for  $v$

$$-v_t + \tilde{H}(x, Dv) - \frac{1}{2\delta} |\sigma(x)^T Dv|^2 = \text{tr} \left( \frac{\sigma \sigma^T(x)}{2} D^2 v \right) \quad \text{in } (0, T) \times \mathbf{R}^d,$$

$$\tilde{H}(x, p) := \sup_{a \in A} [-f(x, a) \cdot p - L(x, a)]$$

with the terminal condition  $v(T, x) = G(x)$ .

This is a H-J equation with a **non-convex** Hamiltonian

$$H = \tilde{H} - |\sigma(x)^T p|^2,$$

perhaps a H-J-Isaacs equation.

A classical Verification Theorem holds, see Fleming and Soner's book.

# Robust control

Now consider the stochastic control system with an additional **disturbance**  $\beta$

$$dX_s = [f(X_s, \alpha_s) + \tau(X_s)\beta_s] ds + \sigma(X_s) dW_s, \quad X_t = x \in \mathbf{R}^d, \quad 0 \leq t \leq T$$

with  $W_s$ ,  $\alpha_s =$ , and  $\sigma$  as before,  $\tau$  a given matrix and  $\beta$  an UNKNOWN disturbance (typically unbounded).

Following Fleming (1960) we can perform a worst case analysis by modelling  $\beta$  as an **adversary playing strategies** (adapted to  $W_s$ ) in a **0-sum** differential game.

The value function is, for  $\delta > 0$

$$V(x) := \inf_{\alpha} \sup_{\beta} E \left[ \int_t^T L(X_s, \alpha_s) - \frac{\delta}{2} |\beta_s|^2 ds + G(X_T) \right]$$

# H-J-Isaacs equation for robust control

The H-J-I equation associated to  $V$  by Dynamic Programming is

$$-v_t + H(x, Dv) = \text{tr} \left( \frac{\sigma \sigma^T(x)}{2} D^2 v \right) \quad \text{in } (0, T) \times \mathbf{R}^d,$$

$$\begin{aligned} H(x, p) &:= \sup_{a \in A} \inf_{b \in \mathbf{R}^m} [-(f(x, a) + \tau(x)b) \cdot p - L(x, a) + \frac{\delta}{2}|b|^2] \\ &= \tilde{H}(x, p) - |\tau(x)^T p|^2 \end{aligned}$$

It is the **same PDE** as in risk-sensitive control if  $\tau = \sigma$  !

So risk-sensitive control can be interpreted as robust control, and both as **0-sum** stochastic differential **games**.

Large engineering literature on these subjects and on the related  $H^\infty$  **control**, see, e.g., Basar and Bernhard's book.



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# Saddle feedback trajectory for the 0-sum game

A **Verification Theorem** holds for the 0-sum stochastic differential game if the H-J-I equation + terminal condition  $v(T, x) = G(x)$  has a smooth solution  $V$ . It produces a saddle point in feedback form.

If  $\tilde{H}$  is smooth and  $\inf_a[\dots]$  is attained at a single point it is also known that the **trajectory** associated to the **saddle strategies** satisfies

$$dX_s = D_p H(X_s, DV(X_s))$$

as in the case of a single player!

This allows to derive, at least formally, the **MFG system** of PDEs for a large population of identical agents with independent Brownian noises and independent deterministic disturbances, see

Tembine, Zhu, Basar 2014 for risk sensitive and  
Bauso, Tembine, Basar 2016 for robust control.

# Robust Mean Field Games

Assume now the cost functional of a representative agent in a population is of the form

$$E \left[ \int_t^T L(X_s, \alpha_s) + F(X_s, m(s, \cdot)) - \frac{\delta}{2} |\beta_s|^2 ds + G(X_T, m(T, \cdot)) \right],$$

where  $F, G : \mathbf{R}^d \times \mathcal{P}(\mathbf{R}^d) \rightarrow \mathbf{R}$  depend on the **distribution of the population** of agents  $m(\cdot, \cdot)$ .

If the agent and the disturbance  $\beta$  "behave optimally", i.e., choose a feedback saddle of their 0-sum game, the probability distribution  $\mu(t, x)$  of the agent solves the Kolmogorov-Fokker-Plank equation

$$\mu_t - \operatorname{div}(D_p H(x, Dv)\mu) = \operatorname{tr} D^2 \left( \frac{\sigma \sigma^T(x)}{2} \mu \right) \quad \text{in } (0, T) \times \mathbf{R}^d$$

Assume also that we are given the initial distribution of the representative agent  $\mu(0, x) = \nu(x)$

# The PDE system for robust MFG

We have an MFG equilibrium if **all players are identical** and "behave **optimally**", so  $\mu(t, x) = m(t, x)$  and it satisfies

$$\left\{ \begin{array}{l} -v_t + H(x, Dv) = \text{tr} \left( \frac{\sigma \sigma^T(x)}{2} D^2 v \right) + F(x, m(t, \cdot)) \quad \text{in } (0, T) \times \mathbf{R}^d, \\ v(T, x) = G(x, m(T, \cdot)) \\ m_t - \text{div}(D_p H(x, Dv)m) = \sum_{i,j} \partial_{ij} \left( \frac{\sigma \sigma^T(x)}{2} \mu \right)_{i,j} \quad \text{in } (0, T) \times \mathbf{R}^d, \\ m(0, x) = \nu(x), \end{array} \right.$$

where

- $H(x, p) := \sup_a [-f(x, a) \cdot p - L(x, a)] - |\tau(x)^T p|^2$
- $v$  is the **value function** of a representative agent.

# Known results

- Tembine, Zhu, Basar 2014: model and numerical simulations for risk-sensitive MFG
- Bauso, Tembine, Basar 2016: same for robust MFG
- Moon, Basar 2017: LQ risk-sensitive and robust MFG
- Tran preprint 2017: existence and uniqueness (small data) for toy model with periodic BC
- Existence for periodic BC and regularity: Some results can be adapted from general theory Lasry - Lions (2006 -... ), Cardaliaguet, Porretta, Gomes and coworkers, etc....
- We are more interested in
  - Neumann boundary conditions in a bounded smooth domain, or
  - problem in **all  $\mathbf{R}^d$**  with growth conditions or integrability conditions at infinity.
- Main difference in the non-convex case: Uniqueness ?

From now on, for simplicity,  $\sigma > 0$  scalar constant.

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# The Lasry-Lions monotonicity condition

A sufficient condition for **uniqueness** of classical solutions is

$$p \rightarrow H(x, p) \text{ convex}$$

$$\int_{\mathbf{R}^n} [F(x, m) - F(x, \bar{m})] d(m - \bar{m})(x) > 0, \forall m \neq \bar{m} \in \mathcal{P}(\mathbf{R}^d)$$

$$\int_{\mathbf{R}^n} [G(x, m) - G(x, \bar{m})] d(m - \bar{m})(x) \geq 0, \forall m, \bar{m} \in \mathcal{P}(\mathbf{R}^d)$$

the **costs** are "increasing with the density" in  $L^2$ .

(See Cardaliaguet's notes for the proof)

## Example

$F$  is "local", i.e.,  $F(\cdot, m)(x) = f(x, m(x))$  and  $f$  is increasing in  $m(x)$ :  
the more is crowded the place where I am, the more I pay.

# A non-local example

Notation: Mean of  $\mu \in \mathcal{P}_1(\mathbb{R}^n)$ ,  $M(\mu) := \int_{\mathbb{R}} y \mu(dy)$ .

Variant of the L-L uniqueness result: replace the strict monotonicity of  $F$  with:  $F$  and  $G$  depend on  $m$  only via  $M(m)$  and

$$\int_{\mathbb{R}^n} [F(x, m) - F(x, \bar{m})] d(m - \bar{m})(x) > 0, \quad \forall M(m) \neq M(\bar{m})$$

## Example

$$F(x, \mu) = \beta x M(\mu), \quad G(x, \mu) = \gamma x M(\mu)$$

$\beta, \gamma \in \mathbf{R}$ . Then

$$\int_{\mathbb{R}^n} [F(x, m) - F(x, \bar{m})] d(m - \bar{m})(x) = \beta (M(m) - M(\bar{m}))^2 \geq 0,$$

and the condition above is satisfied if  $\beta > 0, \gamma \geq 0$ .



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# Uniqueness for non-convex $H$ ?

Lions lecture at College de France 2009: uniqueness for **short horizon**  $T$ .

It turns that variants of that unpublished idea work for

- non-convex but smooth  $H$
- non-monotone costs  $F$  and  $G$ ,
- boundary conditions different from periodic
- smallness of some other data instead of  $T$
- MFG with several populations of agents, i.e. systems of  $n$  HJB and  $n$  KFP equations.

# Thm. [B.-Fischer]: uniqueness for short horizon in $\mathbf{R}^d$

Assume  $H \in C^2$  with respect to  $p$ ,  $\nu \in \mathcal{P} \cap L^\infty(\mathbf{R}^d)$ ,

$$\|F(\cdot, \mu) - F(\cdot, \bar{\mu})\|_2 \leq L_F \|\mu - \bar{\mu}\|_2,$$

$$\|DG(\cdot, \mu) - DG(\cdot, \bar{\mu})\|_2 \leq L_G \|\mu - \bar{\mu}\|_2$$

$(v_1, m_1), (v_2, m_2)$  two classical solutions of the MFG PDEs with  $D(v_1 - v_2) \in L^2([0, T] \times \mathbf{R}^d)$ , and

$$|D_p H(x, Dv_i)|, |D_p^2 H(x, Dv_i)| \leq C_H.$$

Then  $\exists \bar{T} = \bar{T}(d, L_F, L_G, \|\nu\|_\infty, C_H) > 0$  such that  $\forall T < \bar{T}$ ,

$v_1(\cdot, t) = v_2(\cdot, t)$  and  $m_1(\cdot, t) = m_2(\cdot, t)$  for all  $t \in [0, T]$ .

Corollary (Uniqueness for "small data")

*Uniqueness remains true for all  $T > 0$  if either  $L_F, L_G$  are small, or  $\sup |D_p^2 H(x, Dv_i)|$  is small.*

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## Corollary (Uniqueness for "small data")

*Uniqueness remains true for all  $T > 0$  if either  $L_F, L_G$  are **small**, or  $\sup |D_p^2 H(x, Dv_i)|$  is **small**.*

# Sketch of proof

Assume for simplicity  $H = H(p)$  only and  $\sigma = 1$ .

For two solutions  $(v_1, m_1), (v_2, m_2)$  take  $v := v_1 - v_2$ ,  $m := m_1 - m_2$ , write the PDEs for  $(v, m)$ : the 1st is

$$\begin{cases} -v_t + B(t, x) \cdot Dv = \Delta v + F(x, m_1) - F(x, m_2) & \text{in } (0, T) \times \mathbf{R}^d, \\ v(T, x) = G(x, m_1(T)) - G(x, m_2(T)). \end{cases}$$

with  $B(t, x) := \int_0^1 DH(Dv_2 + s(Dv_1 - Dv_2)) ds \in L^\infty((0, T) \times \mathbf{R}^d)$ .

Then by energy estimates we get

$$\begin{aligned} \|Dv(t, \cdot)\|_{L_x^2} &\leq C_1 \int_t^T \|F(\cdot, m_1(s)) - F(\cdot, m_2(s))\|_{L_x^2} ds + \\ &C_2 \|DG(\cdot, m_1(T)) - DG(\cdot, m_2(T))\|_{L_x^2}. \end{aligned}$$

The Lipschitz assumption on  $F$  and  $DG$  implies

$$\|Dv(t, \cdot)\|_{L_x^2} \leq C_1 L_F \int_t^T \|m(s, \cdot)\|_{L_x^2} ds + C_2 L_G \|m(T, \cdot)\|_{L_x^2}$$

Similarly, from the 2nd equation can estimate

$$\|m(t, \cdot)\|_{L_x^2} \leq C_3 \int_0^t \|Dv(s, \cdot)\|_{L_x^2} ds$$

Now set  $\phi(t) := \|Dv(t, \cdot)\|_{L_x^2}$  and combine the inequalities to get

$$\phi(t) \leq C_4 \int_t^T \int_0^\tau \phi(s) ds d\tau + C_5 \int_0^T \phi(s) ds$$

and  $\Phi := \sup_{0 \leq t \leq T} \phi(t)$  satisfies

$$\Phi \leq \Phi(C_4 T^2/2 + C_5 T)$$

so  $\Phi = 0$  for  $T$  small enough.

**Remark:** a crucial estimate is

$$\|m_i(t, \cdot)\|_\infty \leq C(T, \|DH(Dv_i)\|_\infty) \|\nu\|_\infty, \quad i = 1, 2, \quad \forall t \in [0, T],$$

that we prove by probabilistic methods.

Example (Regularizing costs)

$$F(x, \mu) = F_1 \left( x, \int_{\mathbf{R}^d} k_1(x, y) \mu(y) dy \right),$$

with  $k_1 \in L^2(\mathbf{R}^d \times \mathbf{R}^d)$ ,  $|F_1(x, r) - F_1(x, s)| \leq L_1|r - s|$ ;

$$G(x, \mu) = g_1(x) \int_{\mathbf{R}^d} k_2(x, y) \mu(y) dy + g_2(x)$$

with  $g_1, g_2 \in C^1(\mathbf{R}^d)$ ,  $Dg_1$  bounded,  $k_2, D_x k_2 \in L^2(\mathbf{R}^d \times \mathbf{R}^d)$ .



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## Example ( Local costs)

$G = G(x)$  independent of  $m(T)$  and  $F$  of the form

$$F(x, \mu) = f(x, \mu(x))$$

with  $f : \mathbf{R}^d \times [0, +\infty) \rightarrow \mathbf{R}$  such that

$$|f(x, r) - f(x, s)| \leq L_f |r - s| \quad \forall x \in \mathbf{R}^d, r, s \geq 0.$$

Then  $F$  is Lipschitz in  $L^2$  with  $L_F = L_f$ .

Remark: no convexity assumption on  $H$ , nor monotonicity of  $F$  and  $G$ , but the minimal regularity of  $H$  is  $C^{1,1}$  w.r.t.  $p$ .

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Remark: **no convexity** assumption on  $H$ , **nor monotonicity** of  $F$  and  $G$ , but the **minimal regularity** of  $H$  is  $C^{1,1}$  w.r.t.  $p$ .

# More on uniqueness?

**Questions:** are the conditions for uniqueness merely technical or close to necessary? how far from optimal?

Related very recent papers (with periodic BC):

- Cirant, Gianni, Mannucci preprint 2018: short-time existence and uniqueness for parabolic systems more general than MFG
- Cirant, Goffi preprint 2018: short-time existence and uniqueness for MFG with non-local terms.

Nonetheless, are there **examples of multiple solutions**? even for short time horizon?

# Examples of non-uniqueness: stationary MFGs

The stationary MFG PDEs:

$$(MFE) \quad \begin{cases} -\Delta v + H(x, \nabla v) + \lambda = F(x, m) & \text{in } \mathbb{T}^d, \\ \Delta m + \operatorname{div}(\nabla_p H(x, \nabla v)m) = 0 & \text{in } \mathbb{T}^d, \\ \int_{\mathbb{T}^d} m(x) dx = 1, \quad m > 0, \quad \int_{\mathbb{T}^d} v(x) dx = 0, \end{cases}$$

has uniqueness for  $F$  monotone increasing and  $H$  convex. Otherwise:

- Lasry-Lions for  $H(x, p) = |p|^2$  via a Hartree equation of Quantum Mechanics,
- Gueant 2009 for (local) logarithmic utility  $F = -\log m$
- M.B. 2012 and M.B. - F. Priuli 2014 for LQG models in  $\mathbf{R}^d$
- M. Cirant 2015 and Y. Achdou - M.B. - M. Cirant 2016 for systems of **two populations** with Neumann boundary conditions.

**Question:** counter-examples for the **evolutive** case?

**How far** from the monotonicity condition? Also for  $T$  **small**?

# Existence of two solutions

## Theorem (Any $T > 0$ )

Assume  $d = 1$ ,  $H(p) = |p|$ ,  $F, G \in C^1$ ,  $\sigma > 0$  and  $C^2$ ,  $M(\nu) = 0$ , and

$$\frac{\partial F}{\partial x}(x, \mu) \begin{cases} \leq 0 & \text{if } M(\mu) > 0, \\ \geq 0 & \text{if } M(\mu) < 0. \end{cases}$$

$$\frac{\partial G}{\partial x}(x, \mu) \begin{cases} \leq 0 & \text{and not } \equiv 0 & \text{if } M(\mu) > 0, \\ \geq 0 & \text{and not } \equiv 0 & \text{if } M(\mu) < 0, \end{cases}$$

$\implies \exists$  solutions  $(\nu, m)$ ,  $(\bar{\nu}, \bar{m})$  with

$$v_x(t, x) < 0, \quad \bar{v}_x(t, x) > 0 \quad \text{for all } 0 < t < T.$$

- $T > 0$  can also be small:  $H$  convex but not  $C^1$ .
- No assumption on the monotonicity of  $F, G$  w.r.t.  $\mu$ .
- We have also a probabilistic formulation and proof of non-uniqueness under less assumptions on  $\sigma$ .

# Existence of two solutions

## Theorem (Any $T > 0$ )

Assume  $d = 1$ ,  $H(p) = |p|$ ,  $F, G \in C^1$ ,  $\sigma > 0$  and  $C^2$ ,  $M(\nu) = 0$ , and

$$\frac{\partial F}{\partial x}(x, \mu) \begin{cases} \leq 0 & \text{if } M(\mu) > 0, \\ \geq 0 & \text{if } M(\mu) < 0. \end{cases}$$

$$\frac{\partial G}{\partial x}(x, \mu) \begin{cases} \leq 0 & \text{and not } \equiv 0 & \text{if } M(\mu) > 0, \\ \geq 0 & \text{and not } \equiv 0 & \text{if } M(\mu) < 0, \end{cases}$$

$\implies \exists$  solutions  $(\nu, m)$ ,  $(\bar{\nu}, \bar{m})$  with

$$v_x(t, x) < 0, \quad \bar{v}_x(t, x) > 0 \quad \text{for all } 0 < t < T.$$

- $T > 0$  can also be small:  $H$  convex but **not**  $C^1$ .
- No assumption on the monotonicity of  $F, G$  w.r.t.  $\mu$ .
- We have also a **probabilistic** formulation and proof of non-uniqueness under less assumptions on  $\sigma$ .

# Explicit example of non-uniqueness

$$F(x, \mu) = \beta x M(\mu) + f(\mu), \quad G(x, \mu) = \gamma x M(\mu) + g(\mu),$$

with  $\beta, \gamma \in \mathbf{R}$ ,  $f, g : \mathcal{P}_1(\mathbb{R}) \rightarrow \mathbf{R}$ , e.g.,  $f, g$  depend only on the moments of  $\mu$ .

There are **two different solutions** if

$$\beta \leq 0, \quad \gamma < 0,$$

By the L-L monotonicity result there is uniqueness if  $f = g \equiv 0$  and

$$\beta > 0, \quad \gamma \geq 0.$$

If  $\beta < 0, \gamma < 0$   $F$  and  $G$  are not decreasing in  $M(\mu)$ , but an agent has a **negative cost**, i.e., a reward, for having a **position  $x$  with the same sign as the average position  $M(m)$**  of the whole population. Conversely, the conditions for uniqueness express aversion to crowd.



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## Existence of two solutions - 2

Theorem ( $H$  smooth and  $T > \varepsilon$ )

Same assumptions as previous Thm., BUT, for some  $\delta, \varepsilon > 0$ ,

$$H(p) = |p|, \text{ for } |p| \geq \delta$$

$$\frac{\partial G}{\partial x}(x, \mu) \begin{cases} \leq -\delta & \text{if } M(\mu) \geq \varepsilon, \\ \geq \delta & \text{if } M(\mu) \leq -\varepsilon, \end{cases}$$

$\implies$  for  $T \geq \varepsilon \exists$  solutions  $(v, m), (\bar{v}, \bar{m})$  with

$$v_x(t, x) \leq -\delta, \quad \bar{v}_x(t, x) \geq \delta \quad \text{for all } 0 < t < T.$$

Example

$$H(p) := \max_{|\gamma| \leq 1} \left\{ -p\gamma + \frac{1}{2}\delta(1 - \gamma^2) \right\} = \begin{cases} \frac{p^2}{2\delta} + \frac{\delta}{2}, & \text{if } |p| \leq \delta, \\ |p|, & \text{if } |p| \geq \delta, \end{cases}$$

# Idea of proof

$$\begin{cases} -v_t + |v_x| = \frac{\sigma^2(x)}{2} v_{xx} + F(x, m(t, \cdot)), & v(T, x) = G(x, M(m(T))), \\ m_t - (\text{sign}(v_x)m)_x = \left(\frac{\sigma^2(x)}{2}m\right)_{xx}, & m(0, x) = \nu(x). \end{cases}$$

Ansatz:  $\text{sign}(v_x) = -1$  and  $m$  solves

$$m_t + m_x = \left(\frac{\sigma^2(x)}{2}m\right)_{xx}, \quad m(0, x) = \nu(x).$$

Then  $m$  is the law of the process

$$X(t) = X(0) + t + \int_0^t \sigma(X(s))dW(s)$$

with  $X(0) \sim \nu$ , so  $M(m(t)) = \mathbf{E}[X(t)] = M(\nu) + t = t > 0 \quad \forall t$ .

$$(E-) \quad -v_t - v_x = \frac{\sigma^2(x)}{2} v_{xx} + F(x, m), \quad v(T, x) = G(x, m(T)).$$

Then  $w = v_x$  satisfies

$$-w_t - w_x - \sigma \sigma_x w_x - \frac{\sigma^2}{2} w_{xx} = \frac{\partial F}{\partial x}(x, m) \leq 0$$

$$w(T, x) = \frac{\partial G}{\partial x}(x, m(T)) \leq 0 \text{ and not } \equiv 0,$$

Similarly we can build a solution with  $\text{sign}(\bar{v}_x) = 1$  and  $\bar{m}$  solving

$$\bar{m}_t - \bar{m}_x = \frac{\sigma^2(x)}{2} \bar{m}_{xx}, \quad \bar{m}(0, x) = \nu(x),$$

so that  $M(\bar{m}(t, \cdot)) = -t < 0$  and  $\frac{\partial F}{\partial x}(x, \bar{m}(t, \cdot)), \frac{\partial G}{\partial x}(x, \bar{m}(T)) \geq 0$ .

# Other examples of non-uniqueness in finite horizon MFGs

For **periodic** boundary conditions:

- A. Briani, P. Cardaliaguet 2016: for a **potential** MFG
- M. Cirant, D. Tonon 2017: for a **focusing** MFG
- M. Cirant 2018: **bifurcation** of periodic solutions from stationary one.

# Neumann boundary conditions

For  $\Omega$  bounded and smooth,

$$\left\{ \begin{array}{l} -\partial_t v + H(x, Dv) = \Delta v + F(x, m(t, \cdot)) \quad \text{in } (0, T) \times \Omega, \\ v(T, x) = G(x, m(T, \cdot)), \quad \partial_n v = 0 \quad \text{on } \partial\Omega \times (0, T), \\ \partial_t m - \operatorname{div}(D_p H(x, Dv)m) = \Delta m \quad \text{in } (0, T) \times \Omega, \\ m(0, x) = \nu(x), \quad \partial_n m + m D_p H(x, Du) \cdot n = 0 \quad \text{on } \partial\Omega \times (0, T) \end{array} \right.$$

# Theorem [M.B. - M. Cirant]: uniqueness for small data

Assume  $H \in C(\bar{\Omega} \times \mathbf{R}^d)$ ,  $C^2$  in  $p$ ,  $\nu \in \mathcal{P} \cap L^\infty(\Omega)$ ,

$$\|F(\cdot, \mu) - F(\cdot, \bar{\mu})\|_2 \leq L_F \|\mu - \bar{\mu}\|_2,$$

$$\|DG(\cdot, \mu) - DG(\cdot, \bar{\mu})\|_2 \leq L_G (\|\mu - \bar{\mu}\|_2$$

$(\nu, m), (\bar{\nu}, \bar{m})$  two classical solutions and

$$|D_p H(x, D\nu)|, |D_p H(x, D\bar{\nu})| \leq C_1,$$

$$|D_p^2 H(x, D\nu)|, |D_p^2 H(x, D\bar{\nu})| \leq C_2.$$

Then  $\exists \bar{T} = \bar{T}(d, L_F, L_G, \|\nu\|_\infty, C_1, C_2) > 0$  such that  $\forall T < \bar{T}$ ,

$v(\cdot, t) = \bar{v}(\cdot, t)$  and  $m(\cdot, t) = \bar{m}(\cdot, t) \forall t \in [0, T]$ .

The same conclusion holds for all  $T > 0$  if  $L_F$  and  $L_G$  are small, or  $C_2$  is small.



# Remarks

- 1. A crucial estimate for the proof is, for some  $r > 1$ ,  $C > 0$ ,

$$\|m\|_\infty \leq C[1 + \|\nu\|_\infty + (1 + T)\|D_p H(\cdot, D\nu)\|_\infty]^r.$$

- 2. The bound  $\bar{T}$  on the horizon length may depend on the two solution via  $C_1$  and  $C_2$ .

It depends only on the data if we have an a-priori bound on  $D\nu, D\bar{\nu}$ .

This can be got from classical parabolic regularity under, e.g., the additional assumptions

- ▶  $F, G$  bounded, respectively, in  $C^{1,\beta}(\bar{\Omega})$ ,  $C^{2,\beta}(\bar{\Omega})$  uniformly w.r.t.  $m \in \mathcal{P}(\bar{\Omega})$  (regularizing costs)
- ▶  $H \in C^1(\bar{\Omega} \times \mathbf{R}^d)$  with at most quadratic growth

$$|H(x, p)| \leq C_0(1 + |p|^2), \quad |D_p H(x, p)|(1 + |p|) \leq C_0(1 + |p|^2).$$

- 1. A crucial estimate for the proof is, for some  $r > 1$ ,  $C > 0$ ,

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$$|H(x, p)| \leq C_0(1 + |p|^2), \quad |D_p H(x, p)|(1 + |p|) \leq C_0(1 + |p|^2).$$

# Theorem [Y. Achdou - M.B. - M. Cirant]: existence

Assume

- $F, G$  continuous in  $\bar{\Omega} \times \mathcal{P}(\bar{\Omega})$  with the Kantorovich distance,
- $F, G$  **regularizing**, as in Rmk. 2,
- $H \in C^1(\bar{\Omega} \times \mathbf{R}^d)$  with at most **quadratic growth**, as in Rmk. 2,
- $\nu \in C^{2,\beta}(\bar{\Omega})$ .
- **Compatibility conditions** of data at the boundary:  
 $\forall x \in \partial\Omega, \mu \in \mathcal{P}(\bar{\Omega}), u$  with  $\partial_n u(x) = 0$

$$\partial_n G(x, \mu)(x) = 0, \quad \partial_n \nu(x) + \nu D_p H(x, Du(x)) \cdot n = 0.$$

Then  $\forall T > 0$  there **exists a classical solution** of the MFG system with Neumann conditions.

# Robust MFG with Neumann conditions

For the stochastic system with control  $\alpha_s$  and disturbance  $\beta$   
 $d$ -dimensional

$$dX_s = [f(X_s) + g(X_s)\alpha_s + \tau(X_s)\beta_s] ds + dW_s,$$

with  $g$  and  $\tau$  scalar  $C^1$  functions,  $f \in C^1$ , consider the trajectories that are **reflected at the boundary** of  $\Omega$  (Skorokhod problem): this leads to Neumann conditions for the H-J-Isaacs equation.

The functional that  $\alpha$  minimizes and  $\beta$  maximizes is

$$\mathbb{E} \left[ \int_0^T \left( F(X_s, m(s, \cdot)) + \frac{|\alpha_s|^2}{2} - \delta \frac{|\beta_s|^2}{2} \right) ds + G(X_T, m(T, \cdot)) \right]$$

This leads to the Hamiltonian

$$H(x, p) = -f(x) \cdot p + g^2(x) \frac{|p|^2}{2} - \tau^2(x) \frac{|p|^2}{2\delta}.$$

# Corollary: well-posedness for robust MFG system

- Take

$$H(x, p) = -f(x) \cdot p + g^2(x) \frac{|p|^2}{2} - \tau^2(x) \frac{|p|^2}{2\delta},$$

- $F, G$  regularizing and "Lip in  $L^2$ ",
- $\nu \in C^{2,\beta}(\bar{\Omega})$  satisfying the compatibility condition

$$\partial_n \nu(x) - \nu(x) f(x) \cdot n(x) = 0 \quad \forall x \in \partial\Omega.$$

Then

- for all  $T > 0$  there is a classical solution of of the MFG system with Neumann conditions,
- there exists  $\bar{T} > 0$  such that for all  $T \in (0, \bar{T}]$  such solution is unique.
- $T < \bar{T}$  Lipschitz dependence on initial data

$$\|m(t, \cdot) - \bar{m}(t, \cdot)\|_2^2 \leq \frac{C_T}{\delta} \|\nu - \bar{\nu}\|_2^2$$

Motivation for 2 population: models of **segregation** phenomena in urban settlements, inspired by the Nobel laureate T. Schelling:

$$\left\{ \begin{array}{l} -\partial_t v_k + H^k(x, Dv_k) = \Delta v_k + F^k(x, m_1(t, \cdot), m_2(t, \cdot)) \quad \text{in } (0, T) \times \Omega, \\ v_k(T, x) = G^k(x, m_1(T, \cdot), m_2(T, \cdot)), \quad \partial_n v_k = 0 \quad \text{on } \partial\Omega \times (0, T), \\ \partial_t m_k - \operatorname{div}(D_p H^k(x, Dv_k) m_k) = \Delta m_k \quad \text{in } (0, T) \times \Omega, \quad k = 1, 2, \\ m_k(0, x) = \nu_k(x), \quad \partial_n m_k + m_k D_p H^k(x, Du_k) \cdot n = 0 \quad \text{on } \partial\Omega \times (0, T) \end{array} \right.$$

- Same **existence - uniqueness** result as for 1 population, under the same structure conditions;
- the **monotonicity** condition a la Lasry-Lions is very restrictive, makes **no sense** for the segregation model.

# Remarks and perspectives

- We have examples of **non-uniqueness** for 2 populations
- The proof of uniqueness for small data is flexible: it can be used if  $H(x, p) - F(x, m)$  is replaced by  $\mathcal{H}(x, p, m)$  smooth, and in principle also for **mean-field control** (control of McKean-Vlasov SDEs); a hard point is the  $L^\infty$  estimate for  $m(t, \cdot)$ .

## Questions

- The **existence** theory is not complete: results in all  $\mathbf{R}^d$  and for local cost  $F$  are known only for  $H$  convex (Lions, Caradliaguet; Porretta 2016);
- are there examples of non-uniqueness due only to the non-convexity of  $H$ ?
- For **1st order MFG** (no noise) the theory is completely open if  $H$  is not convex (and not coercive).

Thanks for your attention !