Probabilistic approach

Transport approach

Conclusions

Generalized McKean-Vlasov control problems and an application to optimal liquidation

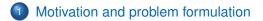
## Beatrice Acciaio London School of Economics

(based on joint works with J. Backhoff and R. Carmona)

"Mathematics and Economics: Trends and Explorations" ETH Zurich, 4-8 June 2018

Transport approach

### Outline



Strong formulation: (classical) probabilistic approach

Weak formulation: (new) optimal transport approach

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# **Motivation**

Conclusions

## N-player stochastic differential game

 $\rightarrow N$  players with **private state processes** evolving as

$$dX_t^i = b(t, X_t^i, \alpha_t^i, \overline{\nu}_t^i)dt + \sigma(t, X_t^i, \alpha_t^i, \overline{\nu}_t^i)dW_t^i, \quad i = 1, ..., N$$

- W<sup>1</sup>, ..., W<sup>N</sup> independent Wiener processes
  α<sup>1</sup>, ..., α<sup>N</sup> controls of the N players
  ν
  <sub>t</sub> = 1/<sub>N-1</sub> Σ<sub>j≠i</sub> δ<sub>X<sub>t</sub><sup>j</sup></sub> empirical distrib. states of the other players
- $\rightarrow$  **Objective of player i**: choose a control  $\alpha^i \in \mathbb{A}$  that minimizes

$$\mathbb{E}\left[\int_0^T f(t,X^i_t,\alpha^i_t,\bar{\boldsymbol{\nu}}^i_t)dt + g(X^i_T,\bar{\boldsymbol{\nu}}^i_T)\right]$$

 $\rightarrow$  Statistically identical players: same functions  $b, \sigma, f, g$ 

Conclusions

### N-player stochastic differential game

 $\rightarrow N$  players with **private state processes** evolving as

$$dX_t^i = b(t, X_t^i, \alpha_t^i, \overline{\xi}_t^i)dt + \sigma(t, X_t^i, \alpha_t^i, \overline{\xi}_t^i)dW_t^i, \quad i = 1, ..., N$$

- $W^1$ , ...,  $W^N$  independent Wiener processes •  $\alpha^1$ , ...,  $\alpha^N$  controls of the *N* players •  $\bar{\xi}_t^i = \frac{1}{N-1} \sum_{j \neq i} \delta_{(X_t^j, a_t^j)}$  empirical distrib. states & controls
- $\rightarrow$  **Objective of player i**: choose a control  $\alpha^i \in \mathbb{A}$  that minimizes

$$\mathbb{E}\left[\int_0^T f(t, X_t^i, \alpha_t^i, \overline{\xi}_t^i) dt + g(X_T^i, \overline{\nu}_T^i)\right]$$

 $\rightarrow$  Statistically identical players: same functions  $b, \sigma, f, g$ 

Conclusions

## N-player stochastic differential game

#### Problems:

- search for equilibria: very difficult
- even when they exist, difficult to characterize

### Idea:

- → for large symmetric games, some averaging/independence are expected when the number of players tends to infinity
- → use theory of propagation of chaos (Sznitman 1991): approximation by asymptotic arguments
- $\hookrightarrow$  formulation of the problem for a representative agent

**Some literature:** Carmona-Delarue (2013), Fischer (2015), Lacker (2015), Lacker (2016)

Transport approach

## Asymptotic argument

N-player game	>	$N \to \infty$
I. Nash equilibrium (competitive)	>	Mean Field Game
II. Pareto equilibrium	>	McKean Vlasov
(cooperative - social planner)		

- $\rightarrow$  **I. Nash equilibrium:** each agent chooses the control as best answer to other agents' actions
- → II. Pareto equilibrium: agents choose their controls so as to minimize their average cost

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# **Problem Formulation**

Conclusions

### Generalized McKean-Vlasov control problem

→ Asymptotic formulation of cooperative equilibria: Generalized McKean-Vlasov control problem:

$$\inf_{\alpha \in \mathbb{A}} \mathbb{E} \left[ \int_0^T f(t, X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)) dt + g(X_T, \mathcal{L}(X_T)) \right]$$

s.t.  $dX_t = b(t, X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)) dt + \sigma(t, X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)) dW_t$ .

- In the asymptotic formulation of **competitive** equilibria (MFG), we would fix any flow of measures (ξ<sub>t</sub>)<sub>0≤t≤T</sub>, and solve the corresponding control problem, then check fixed point.
- Under suitable conditions, the optimal controls are  $\epsilon$ -optimal for large systems of players (cf. Lacker 2016).
- For simplicity from now on we remove the dependence on t

### Generalized McKean-Vlasov control problem

#### Classical approaches for MFG and MKV:

- $\hookrightarrow$  analytic (by PDEs)  $\rightarrow$  HJB equation
- $\hookrightarrow$  probabilistic (by BSDEs)  $\rightarrow$  stochastic maximum principle

### Extensive literature on MFG and MKV:

- Lasry and Lions (2006, 2007)
- Huang, Caines, and Malhamé (2006, 2007)
- Cardaliaguet, Carmona, Delarue, Fischer, Fouque, Lachapelle, Lacker, Lehalle, Pham, Basei, Wei ...

#### Our contribution: allow dependence on the law of the control and

- → probabilistic approach: develop appropriate Pontryagin maximization principle (N&S) in this general framework;
- → optimal transport approach: use dynamic OT to study a weak formulation of the MKV control problem

Probabilistic approach

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# Probabilistic approach

## Probabilistic approach

#### Core concepts:

- Hamiltonian:  $H : \mathbb{R}^d \times \mathbb{R}^k \times \mathcal{P}_2(\mathbb{R}^d \times \mathbb{R}^k) \times \mathbb{R}^d \times \mathbb{R}^{d \times d} \to \mathbb{R}$  $H(x, a, \xi, y, z) = b(x, a, \xi) \cdot y + \sigma(x, a, \xi) \cdot z + f(x, a, \xi)$
- L-differentiability: differentiability w.r.t. laws via lifting functions
   (u : P<sub>2</sub>(ℝ<sup>d</sup> × ℝ<sup>k</sup>) → ℝ L-differentiable at ξ if the lifting function
   ũ : L<sup>2</sup>(Ω, ℱ, ℙ; ℝ<sup>d</sup> × ℝ<sup>k</sup>) ∋ (X̃, α̃) ↦ ũ(X̃, α̃) = u(L(X̃, α̃)) is
   Fréchet differentiable at some (X̃, α̃) with L(X̃, α̃) = ξ)
- for any admissible *α* ∈ A, with *X* = *X<sup>α</sup>* the corresponding controlled state process, the adjoint processes (*Y*, *Z*) satisfy:

$$\begin{cases} dY_t = -\left[\partial_x H(\theta_t, Y_t, Z_t) + \tilde{\mathbb{E}}\left[\partial_v H(\tilde{\theta}_t, \tilde{Y}_t, \tilde{Z}_t)(X_t, \alpha_t)\right]\right] dt + Z_t dW_t, \\ Y_T = \partial_x g(X_T, \mathcal{L}(X_T)) + \tilde{\mathbb{E}}\left[\partial_v g(\tilde{X}_T, \mathcal{L}(X_T))(X_T)\right], \end{cases}$$

where  $\theta_t = (X_t, \alpha_t, \mathcal{L}(X_t, \alpha_t)), \partial_{\nu}, \partial_{\eta}$  deriv. w.r.t.  $\mathcal{L}(X_t), \mathcal{L}(\alpha_t)$ 

## Probabilistic approach

We need the "usual bunch" of **regularity assumptions**: roughly,  $b, \sigma, f, g$  have continuous and bounded derivatives w.r.t.  $x, a, \xi$ .

More precisely:

I. *b*,  $\sigma$ , *f*, *g* differentiable w.r.t. (*x*,  $\alpha$ ), for  $\xi$  fixed, with  $\partial_x$ ,  $\partial_\alpha$  continuous; and L-differentiable w.r.t.  $\xi$ , with  $\partial_v$  continuous.

II.  $\partial_x(b,\sigma)$  and  $\partial_\alpha(b,\sigma)$  uniformly bounded and  $\partial_v(b,\sigma)$  has an  $L^2$ -norm uniformly bounded in  $(x, \alpha, \xi)$ . There exists a constant L such that, for any  $R \ge 0$  and any  $(x, \alpha, \xi)$  s.t.  $|x|, |\alpha|, M_2(\xi) \le R$ , it holds that  $|\partial_x f(x, \alpha, \xi)| \lor |\partial_x g(x, \nu)| \lor |\partial_\alpha f(x, \alpha, \xi)| \le L(1 + R)$ , and the  $L^2$ -norms of  $\partial_v f$  and  $\partial_v g$  are bounded by L(1 + R).

Transport approach

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(\*\*)

### Pontryagin: necessary condition

A: convex set where admissible controls take values

#### Theorem

If  $\alpha$  is optimal, with associated X,Y,Z, then  $\forall a \in A$ , Leb<sub>1</sub>  $\otimes \mathbb{P}$  a.e.,

 $\left(\partial_a H(\theta_t, Y_t, Z_t) + \tilde{\mathbb{E}}\left[\partial_\eta H(\tilde{\theta}_t, \tilde{Y}_t, \tilde{Z}_t)(X_t, \alpha_t)\right]\right) \cdot (\alpha_t - a) \le 0 \qquad (*)$ 

#### Assume

$$\begin{split} H(x,\alpha',\xi',Y,Z) &\geq H(x,\alpha,\xi,Y,Z) + \partial_a H(x,\alpha,\xi,Y,Z) \cdot (\alpha'-\alpha) \\ &\quad + \tilde{\mathbb{E}} \big[ \partial_\eta H(x,a,\xi,Y,Z) (\tilde{X},\tilde{\alpha}) \cdot (\tilde{\alpha}'-\tilde{\alpha}) \big]. \end{split}$$

#### Theorem

Then, if  $\alpha$  is optimal, for Leb<sub>1</sub>-a.e. *t*,  $\alpha_t$  is a minimizer of

 $\inf \left\{ \mathbb{E} \left[ H(X_t, \beta, \mathcal{L}(X_t, \beta), Y_t, Z_t) \right] : \beta \in L^2(\Omega, \mathcal{F}_t, \mathbb{P}) \right\}$ 

## Pontryagin: necessary condition

#### **Remark:**

• In the classical MKV control problem (without dependence on  $\mathcal{L}(\alpha)$ ), the necessary Pontryagin condition reads as

 $H(X_t, \alpha_t, \mathcal{L}(X_t), Y_t, Z_t) \le H(X_t, a, \mathcal{L}(X_t), Y_t, Z_t), \quad \forall a \in A$ 

 $\text{Leb}_1 \otimes \mathbb{P}$  a.e..

In the generalized case, with dependence on *L*(*α*), condition
 (\*\*) cannot be replaced by a pointwise condition.

Transport approach

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### Pontryagin: sufficient condition

#### Assume

$$g(x',\nu') \ge g(x,\nu) + \partial_x g(x,\nu) \cdot (x'-x) + \tilde{\mathbb{E}} \left[ \partial_\nu g(x,\nu) (\tilde{X}) \cdot (\tilde{X}' - \tilde{X}) \right]$$

and

$$\begin{split} H(x',\alpha',\xi',Y,Z) &\geq H(x,\alpha,\xi,Y,Z) + \partial_x H(x,\alpha,\xi,Y,Z) \cdot (x'-x) \\ &\quad + \partial_a H(x,\alpha,\xi,Y,Z) \cdot (\alpha'-\alpha) \\ &\quad + \tilde{\mathbb{E}} \big[ \partial_v H(x,\alpha,\xi,Y,Z) (\tilde{X},\tilde{\alpha}) \cdot (\tilde{X}'-\tilde{X}) \big], \\ &\quad + \tilde{\mathbb{E}} \big[ \partial_\eta H(x,\alpha,\xi,Y,Z) (\tilde{X},\tilde{\alpha}) \cdot (\tilde{\alpha}'-\tilde{\alpha}) \big]. \end{split}$$

#### Theorem

Let  $\alpha$  be any admissible control, with associated *X*, *Y*, *Z*. If (\*) holds, then  $\alpha$  is optimal.

Transport approach

Conclusions

## Example: Linear-Quadratic case

Linear drift:  $b(x, \alpha, \xi) = b_1 x + b_2 \alpha + \bar{b}_1 \bar{x} + \bar{b}_2 \bar{\alpha}$ , where  $\bar{x} = \int \int x\xi(dx, d\alpha)$  and  $\bar{\alpha} = \int \int \alpha x$ 

$$\bar{x} = \iint x\xi(dx, d\alpha) \quad \text{and} \quad \bar{\alpha} = \iint \alpha\xi(dx, d\alpha).$$
Quadratic cost:  $g(x, v) = \frac{1}{2}\gamma x^2 + \frac{\delta}{2}(x - \rho \bar{x})^2 \quad \text{and}$ 

$$f(x, \alpha, \xi) = \frac{1}{2} \Big[ qx^2 + \bar{q}(x - s\bar{x})^2 + r\alpha^2 + \bar{r}(\alpha - \bar{s}\bar{\alpha})^2 \Big].$$

#### The optimal control is

$$\alpha_t = A_t + B_t X_t + C_t \mathbb{E}[X_t],$$

where  $A_t, B_t, C_t$  are solutions of scalar Riccati equations.

## Application: Optimal liquidation problem

- Traders have to buy or sell a large amount of shares between time 0 and time *T* (usually *T* = 1 or *T* = 5, 1 day or 1 week)
- Trades of all market participants reflect on
  - → temporary market impact, influencing the traders' own prices ("cost of liquidity")
  - $\rightarrow$  permanent market impact, influencing the public price
- Optimal execution: tradeoff between trading fast to reduce the risk of future uncertainty in prices, and trading slowly to reduce market impact (or execution/liquidity cost).

**Some literature:** Almgren-Chriss (2000), Cartea-Jaimungal (2015), Cardaliaguet-Lehalle (2017), Basei-Pham (2017)

## Application: Optimal liquidation problem

#### Model:

Inventory:  $dQ_t^i = \alpha_t^i dt$ ,  $Q_0^i = q_0^i$ : initial inventory of agent *i* trading speed

Asset: 
$$dS_t = \lambda \cdot \frac{1}{N} \sum_{i=1}^{N} \alpha_t^i dt + \sigma dW_t$$
,  $S_0 = s_0$   
permanent mk impact

Wealth:  $dU_t^i = -\alpha_t^i (S_t + k \cdot \alpha_t^i) dt$ ,  $U_0^i = 0$ temporary mk impact

Cost to be minimized:

$$\mathbb{E}\left[-\left(U_T^i+Q_T^i(S_T-AQ_T^i)\right)+\phi\int_0^T(Q_t^i)^2dt\right]$$

## Application: Optimal liquidation problem

### Asymptotic formulation:

Asset:  $dS_t = \lambda \mathbb{E}[\alpha_t] dt + \sigma dW_t$ ,  $S_0 = s_0$ Inventory:  $dQ_t = \alpha_t dt$ ,  $Q_0$ : random, initial inventory Wealth:  $dU_t = -\alpha_t(S_t + k\alpha_t) dt$ ,  $U_0 = 0$ 

Problem: 
$$\inf_{\alpha \in \mathbb{A}} \mathbb{E} \left[ -(U_T + Q_T(S_T - AQ_T)) + \phi \int_0^T (Q_t)^2 dt \right]$$

- → Even though this problem does not fall into the above framework, we can still apply our arguments.
- → We can solve the problem and have an explicit formulation of the optimal trading speed and the optimal inventory.

Probabilistic approach

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## Application: Optimal liquidation problem

Optimal trading speed:

 $\begin{array}{l} \alpha_t = \mathbb{E}[\alpha_t] + \underbrace{\varphi_t \left( Q_t - \mathbb{E}[Q_t] \right)}_{\uparrow}, \\ \text{``follow the crowd''} \qquad (\varphi_t \leq 0) \text{ cf. my inventory} \\ \text{with average inventory -} \\ \text{``go against the crowd''} \end{array}$ 

- $\rightarrow$  Cardaliaguet-Lehalle (2017) study the same problem from a competitive point of view, obtaining a similar expression.
- → If agent's position has opposite sign w.r.t. average population, she trades faster; in the framework in [CL17] she trades slower.
- →  $\mathbb{E}[Q_t]$  de/increase slower in our case, i.e.  $|\mathbb{E}[\alpha_t]|$  is smaller: buy/sell market orders arrive "at the same time" (smaller permanent market impact in the cooperative framework).

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# **Optimal Transport approach**

### Weak generalized MKV stochastic control problem

Weak generalized McKean-Vlasov stochastic control problem:

$$\inf_{\mathbb{P},\alpha} \mathbb{E}^{\mathbb{P}} \left[ \int_{0}^{T} f(t, X_{t}, \alpha_{t}, \mathcal{L}_{\mathbb{P}}(X_{t}, \alpha_{t})) dt + g(X_{T}, \mathcal{L}_{\mathbb{P}}(X_{T})) \right]$$
  
subject to  $dX_{t} = b(t, X_{t}, \alpha_{t}, \mathcal{L}_{\mathbb{P}}(X_{t})) dt + dW_{t}^{\mathbb{P}},$ 

 $\rightarrow$  Infimum over filtered probability spaces  $(\Omega, \mathbb{F}, \mathbb{P})$  supporting a Wiener process  $W^{\mathbb{P}}$ , and over  $\alpha$  progress. measurable on  $(\Omega, \mathbb{F}, \mathbb{P})$ .

 $\rightarrow$  Two simplifications here: no dependence on  $\mathcal{L}(\alpha)$  in the drift, and  $\sigma \equiv 1$  (or deterministic).

### Weak generalized MKV stochastic control problem

Weak generalized McKean-Vlasov stochastic control problem:

$$\inf_{\mathbb{P},\alpha} \mathbb{E}^{\mathbb{P}} \left[ \int_{0}^{T} f(t, X_{t}, \alpha_{t}, \mathcal{L}_{\mathbb{P}}(X_{t}, \alpha_{t})) dt + g(X_{T}, \mathcal{L}_{\mathbb{P}}(X_{T})) \right]$$
  
subject to  $dX_{t} = b(t, X_{t}, \alpha_{t}, \mathcal{L}_{\mathbb{P}}(X_{t})) dt + dW_{t}^{\mathbb{P}},$ 

 $\rightarrow$  Infimum over filtered probability spaces  $(\Omega, \mathbb{F}, \mathbb{P})$  supporting a Wiener process  $W^{\mathbb{P}}$ , and over  $\alpha$  progress. measurable on  $(\Omega, \mathbb{F}, \mathbb{P})$ .

 $\rightarrow$  Two simplifications here: no dependence on  $\mathcal{L}(\alpha)$  in the drift, and  $\sigma \equiv 1$  (or deterministic).

Idea: move mass: noise  $\rightarrow$  state

## Monge-Kantorovich optimal transport

**Classical Optimal Transport:**  $(X, \mu), (\mathcal{Y}, \nu)$  Polish, move the mass from  $\mu$  to  $\nu$  minimizing the cost of transportation  $c : X \times \mathcal{Y} \rightarrow [0, \infty]$ :

 $\inf\left\{\mathbb{E}^{\pi}[c(x,y)]:\pi\in\Pi(\mu,\nu)\right\},\$ 

 $\Pi(\mu, \nu)$ : probability measures on  $X \times \mathcal{Y}$  with marginals  $\mu$  and  $\nu$ .

### Extensive literature on OT:

- Monge (1781)
- Kantorovich (1942, 1948)
- Ambrosio, Brenier, Caffarelli, Figalli, Gigli, McCann, Otto, Santabrogio, Sturm, Villani ...
  - $\rightarrow$  We consider a dynamic setting: we have the time component (mathematically: spaces X and  $\mathcal{Y}$  endowed with filtrations)
  - → **Idea**: move the mass in a non-anticipative way: what is transported into the  $2^{nd}$  coordinate at time *t*, depends on the  $1^{st}$  coordinate only up to *t* (+ possibly on sth independent)

Transport approach

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## Causal optimal transport

Definition (Causal transport plans)

 $\pi \in \Pi(\mu, \nu)$  s.t.  $\forall t, D \in \mathcal{F}_t^{\mathcal{Y}}, X \ni x \mapsto \pi^x(D)$  is  $\mathcal{F}_t^X$ -measurable.  $(\mathcal{F}^X, \mathcal{F}^{\mathcal{Y}} \text{ canonical filtrations}, \pi^x \text{ regular conditional kernel})$ 

**Some literature:** Yamada-Watanabe (1971), Jacod (1980), Kurtz (2014), Lassalle (2013), Backhoff-Beiglböck-Lin-Zalashko (2016), Acciaio-Backhoff-Zalashko (2016)

#### Example (Yamada-Watanabe'71)

Assume weak-existence of the solution to the SDE:

 $dY_t = b(Y_t)dt + \sigma(Y_t)dB_t$ ,  $b, \sigma$  Borel measurable.

Then  $\mathcal{L}(B, Y)$  causal transport between  $(C_0, \mathcal{L}(B))$  and  $(C_0, \mathcal{L}(Y))$ .

Here  $X = \mathcal{Y} = C_0 := C_0[0, \infty)$  continuous paths starting at zero

## McKean-Vlasov control problem and Causal Transport

 $\rightarrow$  Recall our weak McKean-Vlasov control problem:

$$\inf_{\mathbb{P},\alpha} \mathbb{E}^{\mathbb{P}} \left[ \int_{0}^{T} f(t, X_{t}, \alpha_{t}, \mathcal{L}_{\mathbb{P}}(X_{t}, \alpha_{t})) dt + g(X_{T}, \mathcal{L}_{\mathbb{P}}(X_{T})) \right]$$
  
subject to  $dX_{t} = b(t, X_{t}, \alpha_{t}, \mathcal{L}_{\mathbb{P}}(X_{t})) dt + dW_{t}^{\mathbb{P}},$ 

→ The joint distribution  $\mathcal{L}(W^{\mathbb{P}}, X)$  is a causal transport plan between  $(C_0[0, T], \gamma)$  and  $(C_0[0, T], \mathcal{L}(X))$ , where  $\gamma$  = Wiener measure on  $C_0[0, T]$ 

## Assumptions

### $\rightarrow$ We need some convexity assumptions:

- b(x, ., v) injective and convex
- f bdd below, and  $f(x, b_t^{-1}(x, ., v)(y), \xi)$  convex in y
- f(x, a, .) is  $\prec_{cm}$ -monotone

In the case of linear drift:

$$dX_t = (c_1X_t + c_2\alpha_t + c_3\mathbb{E}[X_t])dt + dW_t,$$

 $c_i \in \mathbb{R}, c_2 > 0$ , our assumptions reduce to: for all  $x, a, \xi$ :

- *f* is bounded from below
- $f(x, ., \xi)$  is convex
- f(x, a, .) is  $\prec_c$ -monotone

Transport approach

Conclusions

### Characterization via causal optimal transport

→ Here we consider transport problems with  $X = \mathcal{Y} = C_0[0, T]$ , with  $(\omega, \overline{\omega})$  generic element on  $C_0[0, T] \times C_0[0, T]$ 

#### Theorem

The weak MKV problem is equivalent to the variational problem

 $\inf_{\nu \in \mathcal{P}} \inf_{\pi \in \Pi_c(\gamma, \nu)} \mathbb{E}^{\pi} \big[ c(\pi, \omega, \overline{\omega}) \big]$ 

 $\mathcal{P} \text{ is a "good set of measures", } \Pi_{c}(\gamma, \nu) = \{\pi \in \Pi(\gamma, \nu) : \pi \text{ causal}\},\ c(\pi, \omega, \overline{\omega}) = \int_{0}^{T} f(\overline{\omega}_{t}, u_{t}^{\nu}(\omega, \overline{\omega}), p_{t}((\overline{\omega}, u^{\nu})_{\#}\pi)) dt + g(\overline{\omega}_{T}, \nu_{T}), \text{ with}\ u_{t}^{\nu}(\omega, \overline{\omega}) = b_{t}^{-1}(\overline{\omega}_{t}, .., \nu_{t})((\overline{\overline{\omega} - \omega})_{t}) \text{ and } \overline{\omega} - \omega = \int_{0}^{\cdot} (\overline{\overline{\omega} - \omega})_{t} dt$ 

- when control = drift, and square integrable:  $\mathcal{P} = \{ v \ll \gamma \}$
- in general:  $\mathcal{P} = \{ v \in \mathcal{P}(C_0[0, T]) : \langle \omega \rangle \exists v \text{-a.s., with } \langle \omega \rangle_t = t \forall t \},$ where  $\langle \omega \rangle$  is the pathwise quadratic variation

### Characterization via causal optimal transport

#### 'Equivalence' means:

- the above variational problem and the weak MKV problem have the same value;
- and the optimizers are related via:
  - $v^* = \mathcal{L}(X^*)$
  - $\pi^* \longleftrightarrow \alpha^*$ , with  $\pi^* = \mathcal{L}(W^*, X^*)$

#### Corollary (Weak closed loop)

- The infimum can be taken over tuples s.t.  $\alpha$  is  $\mathcal{F}^X$ -measurable (weak closed loop).
- 2 If the infimum is attained, then the optimal control  $\alpha$  is in weak closed loop form.

### Characterization via causal optimal transport

- $\rightarrow$  How to exploit the above characterization?
  - Martingale verification result (analogous of (N) Pontryagin)
  - Discrete-time approximation: we can define transport problems from R<sup>n</sup> to R<sup>n</sup> (via projection) such that their optimal values converge to the original problem
  - New existence and uniqueness results based on tools from optimal transport ...
  - Separable costs Sanov type approximation results ...

## Conclusions

We study generalized McKean-Vlasov control problems, where the mean-field dependence is on both state and control.

### (I) By classical probabilistic approach:

- → Necessary and sufficient Pontryagin conditions in the generalized framework
- $\rightarrow$  Explicitly solvable cases:
  - Linear-Quadratic case
  - Optimal liquidation problem
- (II) By optimal transport approach:
  - → Characterization of weak McKean-Vlasov solutions via causal optimal transport
  - $\rightarrow$  Exploitation of the characterization theorem

Probabilistic approach

Transport approach

Conclusions

## Thank you for your attention!

&

## Happy birthday, Mete!

