

# Mean Field Stackelberg Games: State Feedback Equilibrium

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**Abstract:** We study mean field Stackelberg games between a major player (the leader) and a large population of minor players (the followers). By treating the mean field as part of the dynamics of the major player and a representative minor player, we Markovianize the decision problems and employ dynamic programming to determine the equilibrium strategy in a state feedback form. We show that for linear quadratic (LQ) models, the feedback equilibrium strategy is time consistent. We further give the explicit solution in a discrete-time LQ model.

*Keywords:* Mean field Stackelberg game, feedback strategy, linear-quadratic model, time consistency

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## 1. INTRODUCTION

To tackle complexity in large-population decision problems, mean field games exploit ideas in statistical physics to approximate the collective behavior of a large number of rational agents; see Huang et al. (2006); Lasry and Lions (2006); Cardaliaguet (2013); Caines et al. (2017); Carmona and Delarue (2018). An important generalization of mean field game modeling is to include a major player to interact with a large number of minor players. This is initially introduced in Huang (2010) for an LQ model. Nguyen and Huang (2012) study non-uniform minor players parametrized by a continuum set. Partial information is addressed in Firoozi and Caines (2015). Ma and Huang (2020) apply multi-scale analysis. Important nonlinear extensions are developed by Nourian and Caines (2013); Carmona and Zhu (2016); Lasry and Lions (2018).

For the major-minor player model, a problem of interest is to consider leadership of the major player. In this paper, we will analyze a mean field Stackelberg model with a major player and a large number of minor players. There has been a long history to address leadership in games. Stackelberg competition of a leader and a follower is attributed to von Stackelberg (1934). Başar and Olsder (1999) give a general introduction to dynamic Stackelberg games. Yong (2002) solves an LQ stochastic differential game between a leader and a follower by the stochastic maximum principle. Bensoussan et al. (2015b) derive a maximum principle for stochastic Stackelberg differential games between a leader and a follower under the adapted closed-loop memoryless information structure.

Moon and Başar (2016, 2018) study LQ mean field Stackelberg games in discrete-time and continuous-time settings, respectively. They start with an  $(N + 1)$ -player model and take mean field approximations to derive decentralized strategies. Bensoussan et al. (2015a) study a class of mean field Stackelberg games, in which each minor player has delay in collecting the information of the major player. Bensoussan et al. (2016) study a mean field game model between a (dominating) major player and a continuum of minor players.

The solutions in Bensoussan et al. (2015a, 2016); Moon and Başar (2016, 2018) to various extent rely on calculus of variations or the stochastic maximum principle. The resulting equilibria in general do not have time-consistency. In this mean field game context, a set of strategies is called time consistent if it still has the equilibrium property when implemented in a remaining time horizon. Also see Elie et al. (2019); Fu and Horst (2018) for studying leadership via the stochastic maximum principle. In our work, we introduce a different approach by dynamic programming in an augmented state space so that time consistency can be achieved. Wang and Zhang (2014) use dynamic programming for a discrete time system. But they consider a special class of simple dynamics and costs without control penalty. Their method does not augment the dynamics as in our work and can not handle our model.

Time consistency is an important issue in decision problems including optimal control and dynamic games. Ekeland and Lazrak (2006) analyze a deterministic optimal control problem in continuous time, which has time-inconsistency due to non-exponential discounting. They take a game theoretic point of view by considering  $t$ -selves as different decision makers and characterize a subgame perfect equilibrium. For further references overcoming time-inconsistency, see Ekeland and Pirvu (2008); Björk and Murgoci (2008); Djehiche and Huang (2016); Yong (2017).

### 1.1 Contribution and organization of this paper

Starting from an  $N + 1$  player Stackelberg game, we construct a limiting model with a major player and a representative minor player and look for their equilibrium strategies. Within an augmented state space, we introduce two dynamic programming equations, which can be called the master equations. This paper is organized as follows. Section 2 introduces the finite population Stackelberg game. In Section 3 we study a mean field limit model and obtain feedback strategies. Section 4 solves an LQ model to illustrate the approach in Section 3. Section 5 analyzes a discrete-time LQ mean field limit model.

### 1.2 Notation

Let  $\mathcal{P}_2(\mathbb{R}^n)$  be the set of Borel probability measures on  $\mathbb{R}^n$  with finite second moment;  $C_{b2d}^2(\mathbb{R}^n; \mathbb{R}^k)$  be the set of  $\mathbb{R}^k$ -valued functions with continuous and bounded second order partial derivatives. Denote  $\langle \mu, g \rangle := \int g(y)\mu(dy)$ , and  $\langle y \rangle_\mu := \int y\mu(dy)$  for probability measure  $\mu$  and function  $g$  if the integral is finite. Denote  $|y|_M = (y^T My)^{1/2}$ ,  $\|Y\|_M^2 = Y^T MY$  for  $y \in \mathbb{R}^n$ ,  $Y \in \mathbb{R}^{n \times k}$  and symmetric  $n \times n$  matrix  $M \geq 0$ .

### 2. FINITE-POPULATION STACKELBERG GAME

Let  $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$  be a complete filtered probability space. Consider a major player  $\mathcal{A}_0$  and  $N$  minor players  $\mathcal{A}_i$ ,  $1 \leq i \leq N$ , described by the stochastic differential equations (SDEs):

$$dX_t^0 = f_0(X_t^0, \mu_t^{(N)}, u_t^0)dt + \sigma_0 dW_t^0, \quad (1)$$

$$dX_t^i = f(X_t^0, X_t^i, \mu_t^{(N)}, u_t^0, u_t^i)dt + \sigma dW_t^i, \quad 1 \leq i \leq N, \quad (2)$$

where  $X_t^j \in \mathbb{R}^n$  and  $u_t^j \in \mathbb{R}^{n_1}$  are the state and control of  $\mathcal{A}_j$ ,  $0 \leq j \leq N$ , and  $\mu_t^{(N)} := \frac{1}{N} \sum_{i=1}^N \delta_{X_t^i}$  is the empirical distribution of all minor players' states. All initial states are independent with  $E|X_0^j|^2 \leq C$  for some fixed  $C$ . The  $\mathbb{R}^{n_2}$ -valued Brownian motions  $\{W^j : 0 \leq j \leq N\}$  are mutually independent and also independent of the initial states. The constant matrices  $\sigma_0$  and  $\sigma$  are  $n \times n_2$ . For two closed subsets  $U^0$  and  $U$  of  $\mathbb{R}^{n_1}$ ,  $u_t^0 \in U^0$ ,  $u_t^i \in U$ , for  $1 \leq i \leq N$ . Let  $J_j^{N+1}$  be the cost functional of player  $\mathcal{A}_j$  and

$$J_0^{N+1}(u^0, u^1, \dots, u^N) = E \int_0^T e^{-\rho t} L_0(X_t^0, \mu_t^{(N)}, u_t^0)dt, \quad (3)$$

$$J_i^{N+1}(u^0, u^i, u^{-i}) = E \int_0^T e^{-\rho t} L(X_t^0, X_t^i, \mu_t^{(N)}, u_t^0, u_t^i)dt, \quad (4)$$

where  $\rho > 0$ ,  $1 \leq i \leq N$  and  $u^{-i} = (u^1, \dots, u^{i-1}, u^{i+1}, \dots, u^N)$ . For simplicity, the terminal costs are taken as zero.

On  $\mathcal{P}_2(\mathbb{R}^n)$  we define the Wasserstein metric  $W_2(\mu, \nu) = \inf_{\gamma \in \Gamma(\mu, \nu)} (\int_{\mathbb{R}^{2n}} |x - y|^2 \gamma(dx, dy))^{1/2}$ , where  $\Gamma(\mu, \nu)$  is the set of probability distributions on  $\mathbb{R}^{2n}$  that have  $\mu$  and  $\nu$  as the first and second marginals, respectively. Then  $(\mathcal{P}_2(\mathbb{R}^n), W_2)$  is a complete metric space.

We introduce the following assumption (A1).

(A1) The following functions

$$f_0 : \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n) \times U^0 \rightarrow \mathbb{R}^n, \quad L_0 : \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n) \times U^0 \rightarrow \mathbb{R},$$

$$f : \mathbb{R}^n \times \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n) \times U^0 \times U \rightarrow \mathbb{R}^n,$$

$$L : \mathbb{R}^n \times \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n) \times U^0 \times U \rightarrow \mathbb{R},$$

are continuous, and there exists a constant  $C_0$  such that for  $\phi_f = f_0, f$ , and  $\psi_L = L_0, L$ ,

$$|\phi_f(x_0, x_1, \mu, u_0, u_1) - \phi_f(\hat{x}_0, \hat{x}_1, \hat{\mu}, \hat{u}_0, \hat{u}_1)| \leq C_0(|x_0 - \hat{x}_0| + |x_1 - \hat{x}_1| + |u_0 - \hat{u}_0| + |u_1 - \hat{u}_1| + W_2(\mu, \hat{\mu})),$$

$$|\psi_L(x_0, x_1, \mu, u_0, u_1)| \leq C_0(1 + |x_0|^2 + |x_1|^2 + |u_0|^2 + |u_1|^2 + \langle |y|^2 \rangle_\mu),$$

$$\forall x_0, \hat{x}_0, x_1, \hat{x}_1 \in \mathbb{R}^n, \forall \mu, \hat{\mu} \in \mathcal{P}_2(\mathbb{R}^n), (u_0, u_1) \in U^0 \times U.$$

Denote  $\mathbf{X}_t = (X_t^0, \dots, X_t^N)$ . If we choose  $u_t^0$  and  $u_t^i$  as continuous functions of  $(t, \mathbf{X}_t)$ , with Lipschitz continuity in  $\mathbf{X}_t$ , then the SDE system (1)-(2) has a well defined solution.

A basic solution of the Stackelberg game is to consider state feedback strategies. For the major player, as the leader, and  $N$  minor players, one may try to adapt the dynamic programming approach in Başar and Olsder (1999) for a two-player Stackelberg game. This method, however, becomes unfeasible for large  $N$  due to high complexity.

### 3. MEAN FIELD LIMIT MODEL

Based on the  $(N + 1)$ -player game, we consider a mean field limit Stackelberg model which involves the major player  $\mathcal{A}_0$ , a representative minor player  $\mathcal{A}_1$ , and the distribution  $\mu_t$  determined by a continuum of minor players. Fix  $u_t^0 \equiv u^0$  and  $u_t^i \equiv u$  in (1)-(2). For  $g \in C_{b2d}^2(\mathbb{R}^n)$ , by Itô's formula we have

$$d\langle \mu_t^{(N)}, g \rangle = \langle \mu_t^{(N)}, g'(\cdot) f(X_t^0, \cdot, \mu_t^{(N)}, u^0, u) + \frac{1}{2} \text{Tr}[g''(\cdot) \sigma \sigma^T] \rangle dt + \frac{1}{N} \sum_{i=1}^N g'(X_t^i) \sigma dW_t^i. \quad (5)$$

We consider the following system:

$$dX_s^0 = f_0(X_s^0, \mu_s, u_s^0)dt + \sigma_0 dW_s^0, \quad (6)$$

$$dX_s^1 = f(X_s^0, X_s^1, \mu_s, u_s^0, u_s^1)ds + \sigma dW_s^1, \quad (7)$$

$$\frac{d}{ds} \int_{\mathbb{R}^n} g(y) \mu_s(dy) = \int_{\mathbb{R}^n} [f^T(X_s^0, y, \mu_s, u_s^0, u_s^1) g'(y) + \frac{1}{2} \text{Tr}(g''(y) \sigma \sigma^T)] \mu_s(dy), \quad (8)$$

where  $s \geq t$ ,  $X_t^0 = x_0$ ,  $X_t^1 = x_1$ ,  $\mu_t = \mu \in \mathcal{P}_2(\mathbb{R}^n)$ , and  $g \in C_{b2d}^2(\mathbb{R}^n)$ . Equations (6)-(7) are obtained from (1)-(2) after approximating  $\mu_t^{(N)}$  by  $\mu_t$ . The measure flow  $\{\mu_t, t \geq 0\}$  on one hand drives the evolution of  $(X_s^0, X_s^1)$ , and on the other is regenerated by the empirical distribution of a large population of similar minor players with appropriate initial states. The differential equation (8) for  $\mu_s$  in a weak form, which may be viewed as a limiting form of (5), essentially results from (7). It is informative to list it separately. Due to the arbitrary choice of  $x_1$  and  $\mu$ ,  $\mu_s$  in general is not equal to the distribution (or the conditional distribution given  $\{X_h^0, h \leq s\}$ ) of  $X_s^1$ .

Similarly we define

$$J_0(t, x_0, \mu, u^0, u^1) = E \int_t^T e^{-\rho(s-t)} L_0(X_s^0, \mu_s, u_s^0) ds, \quad (9)$$

$$J_1(t, x_0, x_1, \mu, u^0, u^1) = E \int_t^T e^{-\rho(s-t)} L(X_s^0, X_s^1, \mu_s, u_s^0, u_s^1) ds. \quad (10)$$

We view  $(X_t^0, X_t^1, \mu_t)$  as a state variable and look for feedback strategies of the following form,  $u^0 : [0, T] \times \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n) \rightarrow U^0$ , and  $u^1 : [0, T] \times \mathbb{R}^n \times \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n) \rightarrow U$ . The pair of strategies is admissible if the resulting closed loop system has a well defined solution. Let the value functions be

$$V_0(t, x_0, \mu) = J_0(t, x_0, \mu, u^{0*}, u^{1*}), \quad (11)$$

$$V_1(t, x_0, x_1, \mu) = J_1(t, x_0, x_1, \mu, u^{0*}, u^{1*}). \quad (12)$$

Below we elaborate on the determination of the Stackelberg strategies  $(u^{0*}, u^{1*})$  by dynamic programming equations of the value functions. The reader may consult (Başar and Olsder, 1999, sec. 7.6) for this approach applied to two-player Stackelberg differential games. Define the following differential operators associated with the processes (6)-(7):

$$\begin{aligned}\mathcal{L}_0^{u^0} \cdot &= f_0^T(x_0, \mu, u^0) \frac{\partial}{\partial x_0} \cdot + \frac{1}{2} \text{Tr}[(\frac{\partial^2}{\partial x_0^2}) \sigma_0 \sigma_0^T], \\ \mathcal{L}_1^{u^0, u^1} \cdot &= f^T(x_0, x_1, \mu, u^0, u^1) \frac{\partial}{\partial x_1} \cdot + \frac{1}{2} \text{Tr}[(\frac{\partial^2}{\partial x_1^2}) \sigma \sigma^T], \\ \mathcal{L}_{\text{mf}}^{u^0, u^1} \cdot &= f^T(x_0, y, \mu, u^0, u^1) \frac{\partial}{\partial y} \cdot + \frac{1}{2} \text{Tr}[(\frac{\partial^2}{\partial y^2}) \sigma \sigma^T].\end{aligned}$$

The mean field Stackelberg equilibrium  $(u^{0*}, u^{1*})$ , if it exists, is characterized by the Hamilton-Jacobi-Bellman (HJB) equation system

$$\begin{cases} \rho V_1 = \frac{\partial V_1}{\partial t} + L(x_0, x_1, \mu, u^{0*}, u^{1*}) + (\mathcal{L}_0^{u^{0*}} + \mathcal{L}_1^{u^{0*}, u^{1*}}) V_1 \\ \quad + \int_{\mathbb{R}^n} \mathcal{L}_{\text{mf}}^{u^{0*}, u^{1*}} \partial_\mu V_1(t, x_0, x_1, \mu; y) \mu(dy), \\ \rho V_0 = \frac{\partial V_0}{\partial t} + L_0(x_0, \mu, u^{0*}) + \mathcal{L}_0^{u^{0*}} V_0 \\ \quad + \int_{\mathbb{R}^n} \mathcal{L}_{\text{mf}}^{u^{0*}, u^{1*}} \partial_\mu V_0(t, x_0, \mu; y) \mu(dy), \end{cases} \quad (13)$$

where  $(t, x_0, x_1, \mu) \in [0, T] \times \mathbb{R}^n \times \mathbb{R}^n \times \mathcal{P}_2(\mathbb{R}^n)$  and  $V_1 = V_0 = 0$  at  $t = T$ . We may also call them the master equations.

Here  $\mathcal{L}_{\text{mf}}^{u^0, u^1}$  acts on  $\partial_\mu V_i$ ,  $i = 0, 1$  via the  $y$  variable, with  $(t, x_0, x_1, \mu)$  fixed. Note that  $\partial_\mu V_i$  has the extra independent variable  $y$ . For instance, for a fixed continuous function  $g$  of quadratic growth,  $G(\mu) = \int g(x) \mu(dx)$  is a function of  $\mu \in \mathcal{P}_2(\mathbb{R}^n)$ . Then  $\partial_\mu G(\mu) = g(\cdot)$ . For related references, see Cardaliaguet et al. (2015); Huang (2019). For this section, we make the hypotheses i) the value functions  $V_0$  and  $V_1$  have sufficient smoothness; ii) the derivatives  $\partial_\mu V_0$ ,  $\partial_\mu V_1$  exist and have sufficient smoothness with respect to  $y$ ; iii) integral terms involve functions of mild growth rate to ensure a well defined term; iv) the minimizers in (14)-(15) below are well defined.

These hypotheses are satisfied by the LQ model in Section 4.

For each  $u^0 \in U^0$ , let  $\hat{u}^1$  be the best response of the continuum of minor players including  $\mathcal{A}_1$ . We determine  $\hat{u}^1$  by studying the optimizing behavior of  $\mathcal{A}_1$ . Denote

$$\begin{aligned}H_1 &= L(x_0, x_1, \mu, u^0, u^1) + (\mathcal{L}_0^{u^0} + \mathcal{L}_1^{u^0, u^1}) V_1(t, x_0, x_1, \mu) \\ &\quad + \int_{\mathbb{R}^n} \mathcal{L}_{\text{mf}}^{u^0, \hat{u}^1} \partial_\mu V_1(t, x_0, x_1, \mu; y) \mu(dy),\end{aligned}$$

where  $\hat{u}^1$  has been applied by all other minor players to determine the mean field. Player  $\mathcal{A}_1$  optimizes  $u^1$  only through  $L$  and  $\mathcal{L}_1^{u^0, u^1} V_1(t, x_0, x_1, \mu)$ . Let the minimizer of  $H_1$  be

$$\hat{u}^1 = \varphi_1(x_0, x_1, \mu, u^0, \frac{\partial V_1}{\partial x_1}), \quad (14)$$

which is the best response of  $\mathcal{A}_1$  at  $(t, x_0, x_1, \mu)$  to  $u^0 \in U^0$ .

Next we consider the major player's optimizer when all minor players have adopted (14) by matching their own states. Denote

$$\begin{aligned}H_0 &= L_0(x_0, \mu, u^0) + \mathcal{L}_0^{u^0} V_0(t, x_0, \mu) \\ &\quad + \int_{\mathbb{R}^n} \mathcal{L}_{\text{mf}}^{u^0, \hat{u}^1} \partial_\mu V_0(t, x_0, \mu; y) \mu(dy).\end{aligned}$$

Let the minimizer of  $H_0$  be

$$u^{0*} = \varphi_0(x_0, \mu, \frac{\partial V_0}{\partial x_0}, \partial_\mu V_0(t, x_0, \mu; \cdot), \frac{\partial V_1}{\partial x_1}(t, x_0, \cdot, \mu)). \quad (15)$$

Substituting (15) into (14) gives

$$u^{1*} = \varphi_1(x_0, x_1, \mu, u^{0*}, \frac{\partial V_1}{\partial x_1}). \quad (16)$$

The selection of  $(u^{0*}, u^{1*})$  may be viewed as optimization problems of  $t$ -selves. For instance, given  $(t, x_0, x_1, \mu)$ , a coalition of minor players, i.e.,  $s$ - $\mathcal{A}^1$  agents with  $s \in [t, t + \epsilon]$ , optimizes its cost defined on  $[t, T]$  while it only acts on  $[t, t + \epsilon]$ . Then we let  $\epsilon \rightarrow 0$ . The pair (15)-(16) is called a feedback

Stackelberg equilibrium strategy for the mean field Stackelberg game specified by (6)-(8) and (9)-(10). Under the equilibrium strategy (15)-(16), we may further write the closed-loop dynamics for  $(X_s^0, X_s^1, \mu_s)$ . This section only constructs the HJB equations (13). The existence analysis for these equations together with the closed loop system is an interesting subject. We will not give in-depth analysis here, but will use the LQ case to illustrate computations.

*Remark 1.* We give some detail about the integral terms in (13). Let  $u^0$  be fixed. On  $[t, t + \epsilon]$ , we take a Taylor expansion of  $V_1(t + \epsilon, X_{t+\epsilon}^0, X_{t+\epsilon}^1, \mu_{t+\epsilon})$ . In particular, we have the first order approximation term

$$\begin{aligned}&\int_{\mathbb{R}^n} (\partial_\mu V_1)(t, x_0, x_1, \mu; y) (\mu_{t+\epsilon}(dy) - \mu(dy)) \\ &= \int_{\mathbb{R}^n} f^T(x_0, y, \mu, u^0, \hat{u}^1) \frac{\partial}{\partial y} (\partial_\mu V_1)(t, x_0, x_1, \mu; y) \mu(dy) \epsilon \\ &\quad + \int_{\mathbb{R}^n} \frac{1}{2} \text{Tr}[(\frac{\partial^2}{\partial y^2}) (\partial_\mu V_1)(t, x_0, x_1, \mu; y) \sigma \sigma^T] \mu(dy) \epsilon + o(\epsilon).\end{aligned}$$

In the end,  $(u^0, \hat{u}^1)$  will be taken as  $(u^{0*}, u^{1*})$ . The integral term in the HJB equation of  $V_0$  arises for similar reasons.

#### 4. LINEAR QUADRATIC MEAN FIELD LIMIT MODEL

We consider an LQ mean field limit model, and follow the steps in Section 3 to search for an explicit solution of the mean field Stackelberg equilibrium. Now equations (6)-(7) take drift terms

$$\begin{aligned}f_0(X_t^0, \mu_t, u_t^0) &= A_0 X_t^0 + B_0 u_t^0 + F_0 \langle y \rangle_{\mu_t}, \\ f(X_t^0, X_t^1, \mu_t, u_t^0, u_t^1) &= A X_t^1 + B u_t^1 + D u_t^0 + F \langle y \rangle_{\mu_t} + G X_t^0.\end{aligned}$$

The instantaneous cost functions take the quadratic forms

$$L_0(X_t^0, \mu_t, u_t^0) = |X_t^0 - \Gamma_0 \langle y \rangle_{\mu_t}|_{Q_0}^2 + |u_t^0|_{R_0}^2, \quad (17)$$

$$\begin{aligned}L(X_t^0, X_t^1, \mu_t, u_t^0, u_t^1) &= |X_t^1 - \Gamma_1 X_t^0 - \Gamma_2 \langle y \rangle_{\mu_t}|_Q^2 \\ &\quad + |u_t^1|_{R_1}^2 + |u_t^0|_{R_2}^2 + 2u_t^{0T} R_2 u_t^1.\end{aligned} \quad (18)$$

The matrices  $A_0, A, B_0, B, F_0, F, D, G, \Gamma_0, \Gamma_1, \Gamma_2, Q_0, Q, R > 0, R_0 > 0, R_1$  and  $R_2$  have compatible dimensions.

##### 4.1 Stackelberg equilibrium strategy

Denote  $\tilde{D} = D - BR^{-1}R_2^T$ . By (15)-(16), the Stackelberg equilibrium strategy is

$$u^{0*} = -\frac{1}{2} R_0^{-1} [B_0^T \frac{\partial V_0}{\partial x_0} + \tilde{D}^T \int_{\mathbb{R}^n} \frac{\partial}{\partial y} (\partial_\mu V_0) \mu(dy)], \quad (19)$$

$$u^{1*} = -\frac{1}{2} R^{-1} [B^T \frac{\partial V_1}{\partial x_1} + 2R_2^T u^{0*}]. \quad (20)$$

As a special case of (13), the HJB equations are

$$\begin{aligned}\rho V_0 &= \frac{\partial V_0}{\partial t} + (\frac{\partial V_0}{\partial x_0})^T (A_0 x_0 + B_0 u^{0*} + F_0 \langle y \rangle_\mu) \\ &\quad + \int_{\mathbb{R}^n} (G x_0 + A x_1 + F \langle y \rangle_\mu + B u^{1*} + D u^{0*})|_{x_1=y}^T \\ &\quad \frac{\partial}{\partial y} (\partial_\mu V_0) \mu(dy) + L_0(x_0, \mu, u^{0*}) \\ &\quad + \frac{1}{2} \text{Tr}[(\frac{\partial^2 V_0}{\partial x_0^2}) \sigma_0 \sigma_0^T + \int_{\mathbb{R}^n} \frac{\partial^2}{\partial y^2} (\partial_\mu V_0) \sigma \sigma^T \mu(dy)],\end{aligned} \quad (21)$$

$$\begin{aligned} \rho V_1 = & \frac{\partial V_1}{\partial t} + \left(\frac{\partial V_1}{\partial x_0}\right)^T (A_0 x_0 + B_0 u^{0*} + F_0 \langle y \rangle_\mu) \\ & + \left(\frac{\partial V_1}{\partial x_1}\right)^T (G x_0 + A x_1 + F \langle y \rangle_\mu + B u^{1*} + D u^{0*}) \\ & + \int_{\mathbb{R}^n} (G x_0 + A x_1 + F \langle y \rangle_\mu + B u^{1*} + D u^{0*})|_{x_1=y}^T \\ & \frac{\partial}{\partial y} (\partial_\mu V_1) \mu(dy) + L(x_0, x_1, \mu, u^{0*}, u^{1*}) \\ & + \frac{1}{2} \text{Tr} \left[ \frac{\partial^2 V_1}{\partial x_0^2} \sigma_0 \sigma_0^T + \frac{\partial^2 V_1}{\partial x_1^2} \sigma \sigma^T + \int_{\mathbb{R}^n} \frac{\partial^2}{\partial y^2} (\partial_\mu V_1) \sigma \sigma^T \mu(dy) \right]. \end{aligned} \quad (22)$$

Assume  $V_0$  and  $V_1$  take the following forms

$$\begin{aligned} V_0(t, x_0, \mu) = & x_0^T P_0^0(t) x_0 + \langle y \rangle_\mu^T P_1^0(t) \langle y \rangle_\mu \\ & + 2x_0^T P_{01}^0(t) \langle y \rangle_\mu + r_0(t), \end{aligned} \quad (23)$$

$$\begin{aligned} V_1(t, x_0, x_1, \mu) = & x_0^T P_0(t) x_0 + x_1^T P_1(t) x_1 + \langle y \rangle_\mu^T P_2(t) \langle y \rangle_\mu \\ & + 2(x_0^T P_{01}(t) x_1 + x_0^T P_{02}(t) \langle y \rangle_\mu + x_1^T P_{12}(t) \langle y \rangle_\mu) + r_1(t). \end{aligned} \quad (24)$$

We substitute (23)-(24) into (19)-(20) to obtain

$$u^{0*} = K_0^0 x_0 + K_1^0 \langle y \rangle_\mu, \quad (25)$$

$$u^{1*} = K_0 x_0 + K_1 x_1 + K_2 \langle y \rangle_\mu, \quad (26)$$

where

$$\begin{aligned} K_0^0 &= -R_0^{-1} (B_0^T P_0^0 + \tilde{D}^T P_{01}^{0T}), \\ K_1^0 &= -R_0^{-1} (B_0^T P_{01}^0 + \tilde{D}^T P_1^0), \\ K_0 &= -R^{-1} (R_2^T K_0^0 + B^T P_{01}^T), \\ K_1 &= -R^{-1} B^T P_1, \quad K_2 = -R^{-1} (R_2^T K_1^0 + B^T P_{12}). \end{aligned}$$

The pair  $(u^{0*}, u^{1*})$  obtained by (25)-(26) is a feedback Stackelberg equilibrium. Substituting (23)-(26) into (21)-(22) gives the following Riccati ODE system on  $[0, T]$ :

$$\begin{aligned} \dot{P}_0 = & \rho P_0 - P_0 (A_0 + B_0 K_0^0) - (A_0 + B_0 K_0^0)^T P_0 \\ & - (P_{01} + P_{02})(G + BK_0 + DK_0^0) \\ & - (G + BK_0 + DK_0^0)^T (P_{01} + P_{02})^T \\ & - K_0^{0T} R_2 K_0 - K_0^T R_2^T K_0^0 - \llbracket K_0^0 \rrbracket_R^2 - \llbracket K_0^0 \rrbracket_{R_1}^2 - \llbracket \Gamma_1 \rrbracket_Q^2, \end{aligned}$$

$$\dot{P}_1 = \rho P_1 - P_1 (A + BK_1) - (A + BK_1)^T P_1 - \llbracket K_1 \rrbracket_R^2 - Q,$$

$$\begin{aligned} \dot{P}_2 = & \rho P_2 - P_{02}^T (B_0 K_1^0 + F_0) - (B_0 K_1^0 + F_0)^T P_{02} \\ & - P_{12}^T (BK_2 + DK_1^0 + F) - (BK_2 + DK_1^0 + F)^T P_{12} \\ & - (A + BK_1 + BK_2 + DK_1^0 + F)^T P_2 \\ & - P_2 (A + BK_1 + BK_2 + DK_1^0 + F) \\ & - \llbracket K_2 \rrbracket_R^2 - \llbracket K_1^0 \rrbracket_{R_1}^2 - K_1^{0T} R_2 K_2 - K_2^T R_2^T K_1^0 - \llbracket \Gamma_2 \rrbracket_Q^2, \end{aligned}$$

$$\begin{aligned} \dot{P}_{01} = & \rho P_{01} - (A_0 + B_0 K_0^0)^T P_{01} - P_{01} (A + BK_1) \\ & - (G + BK_0 + DK_0^0)^T (P_1 + P_{12}^T) - K_0^T R K_1 \\ & - K_0^{0T} R_2 K_1 + \Gamma_1^T Q, \end{aligned}$$

$$\begin{aligned} \dot{P}_{02} = & \rho P_{02} - 2P_0 (B_0 K_1^0 + F_0) - (A_0 + B_0 K_0^0)^T P_{02} \\ & - P_{01} (BK_2 + DK_1^0 + F) \\ & - (G + BK_0 + DK_0^0)^T (P_{12} + P_2) \\ & - P_{02} (A + BK_1 + BK_2 + DK_1^0 + F) - K_0^T R K_2 \\ & - K_0^{0T} R_1 K_1^0 - K_0^{0T} R_2 K_2 - K_0^T R_2^T K_1^0 - \Gamma_1^T Q \Gamma_2, \end{aligned}$$

$$\begin{aligned} \dot{P}_{12} = & \rho P_{12} - P_{01}^T (B_0 K_1^0 + F_0) - P_1 (BK_2 + DK_1^0 + F) \\ & - P_{12} (A + BK_1 + BK_2 + DK_1^0 + F) \\ & - (A + BK_1)^T P_{12} - K_1^T R K_2 - K_1^T R_2^T K_1^0 + Q \Gamma_2, \end{aligned}$$

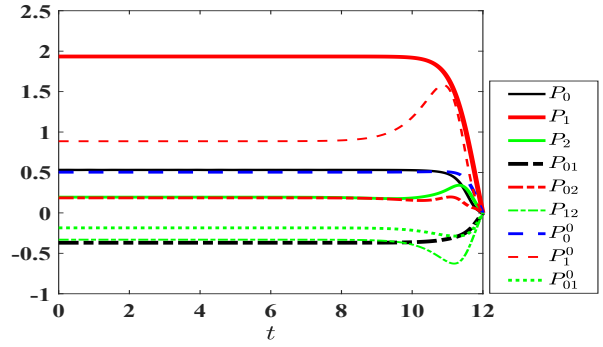


Fig. 1. The solution of  $P_0, P_1, \dots, P_{01}^0$  in Section 4.3.

$$\begin{aligned} \dot{P}_0^0 = & \rho P_0^0 - P_0^0 (A_0 + B_0 K_0^0) - (A_0 + B_0 K_0^0)^T P_0^0 \\ & - P_{01}^0 (G + BK_0 + DK_0^0) - (G + BK_0 + DK_0^0)^T P_{01}^{0T} \\ & - \llbracket K_0^0 \rrbracket_{R_0}^2 - Q_0, \\ \dot{P}_1^0 = & \rho P_1^0 - P_{01}^{0T} (B_0 K_0^0 + F_0) - (B_0 K_0^0 + F_0)^T P_{01}^0 \\ & - (A + BK_1 + BK_2 + DK_1^0 + F)^T P_1^0 \\ & - P_1^0 (A + BK_1 + BK_2 + DK_1^0 + F) - \llbracket K_1^0 \rrbracket_{R_0}^2 - \llbracket \Gamma_0 \rrbracket_{Q_0}^2, \\ \dot{P}_{01}^0 = & \rho P_{01}^0 - P_0^0 (B_0 K_1^0 + F_0) - (A_0 + B_0 K_0^0)^T P_{01}^0 \\ & - P_{01}^0 (A + BK_1 + BK_2 + DK_1^0 + F) \\ & - (G + BK_0 + DK_0^0)^T P_1^0 - K_0^{0T} R_0 K_1^0 + Q_0 \Gamma_0, \end{aligned} \quad (27)$$

where all of  $P_0, P_1, \dots, P_{01}^0$  are equal to 0 at  $T$ .

**Theorem 1.** If the Riccati ODE system (27) has a solution on  $[0, T]$ , then (25)-(26) is a feedback Stackelberg equilibrium on  $[0, T]$ .  $\square$

If (27) has a solution on  $[0, T]$ , the closed-loop system of  $(X_s^0, X_s^1)$  under (25)-(26) admits a unique strong solution.

#### 4.2 Time consistency

A strategy is called time consistent on  $[0, T]$ , if for any subgame on  $[t_1, T], \forall t_1 \in (0, T)$ , it is still an equilibrium.

**Theorem 2.** If the ODE system (27) has a solution on  $[0, T]$ , the Stackelberg equilibrium strategy (25)-(26) is time consistent.

**Proof.** When one restricts to a remaining period  $[t_0, T]$  for any  $t_0 \in (0, T)$  and re-solves a mean field Stackelberg game, the same Riccati ODE system is still valid.  $\square$

#### 4.3 Numerical illustration

MatLab ODE solver `ode45` is used to solve the ODE system (27) of  $P_0, P_1, \dots, P_{01}^0$  on  $[0, T]$ , with terminal condition 0 and parameter values  $A_0 = 1, B_0 = 2, F_0 = 0.5, A = 0.5, B = 1, D = 1, F = 0.2, G = 0.4, \Gamma_0 = 0.8, \Gamma_1 = 0.3, \Gamma_2 = 0.5, Q = 2, Q_0 = 1, R = 1, R_0 = 0.5, R_1 = 1, R_2 = 0.5, T = 12$ , and  $\rho = 0.1$ . The solution is shown in Fig. 1

### 5. DISCRETE-TIME MEAN FIELD LIMIT MODEL

Consider a mean field Stackelberg game with discrete time horizon  $\{0, 1, \dots, T\}$ . The major player  $\mathcal{A}_0$ , a representative minor player  $\mathcal{A}_1$ , and the mean field state  $\bar{X}$  have the dynamics:

$$X_{t+1}^0 = A_0 X_t^0 + B_0 u_t^0 + F_0 \bar{X}_t + W_t^0, \quad (28)$$

$$X_{t+1}^1 = A X_t^1 + B u_t^1 + D u_t^0 + F \bar{X}_t + G X_t^0 + W_t^1, \quad (29)$$

$$\bar{X}_{t+1} = (A + F) \bar{X}_t + B \bar{u}_t + D u_t^0 + G X_t^0, \quad (30)$$

where  $W_t^i$ ,  $0 \leq t \leq T - 1$  are i.i.d. random variables with zero mean and finite variance. The control mean field  $\bar{u}_t = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N u_t^i$ , where each  $u_t^i$  is a minor player's control. For discount factor  $\alpha \in (0, 1)$ , the cost functionals are

$$J_0(u^0, u^1) = E \left[ \sum_{t=0}^{T-1} \alpha^t (|X_t^0 - \Gamma_0 \bar{X}_t|_{Q_0}^2 + |u_t^0|_{R_0}^2) \right], \quad (31)$$

$$J_1(u^0, u^1) = E \left[ \sum_{t=0}^{T-1} \alpha^t (|X_t^1 - \Gamma_1 X_t^0 - \Gamma_2 \bar{X}_t|_{Q_1}^2 + |u_t^1|_R^2 + |u_t^0|_{R_1}^2 + 2u_t^{0T} R_2 u_t^1) \right], \quad (32)$$

*Remark 2.* The underlying  $N + 1$  player model is specified by replacing  $\bar{X}_t$  by  $X_t^{(N)} = \frac{1}{N} \sum_{i=1}^N X_t^i$  in (28)-(29) and  $J_0, J_1$ .

### 5.1 Minimizer of the minor player

By dynamic programming,

$$V_1(t, x_0, x_1, \bar{x}) = \min_{u^1} \{ |X_t^1 - \Gamma_1 X_t^0 - \Gamma_2 \bar{X}_t|_Q^2 + |u_t^1|_R^2 + |u_t^0|_{R_1}^2 + 2u_t^{0T} R_2 u_t^1 + \alpha E[V_1(t+1, X_{t+1}^0, X_{t+1}^1, \bar{X}_{t+1})] \}_{(X_t^0, X_t^1, \bar{X}_t) = (x_0, x_1, \bar{x})}. \quad (33)$$

Given  $u_t^0 = u^0$  for the major player, we assume for  $k = t + 1$ ,

$$V_1(k, x_0, x_1, \bar{x}) = x_0^T \Phi_{0,k} x_0 + x_1^T \Phi_{1,k} x_1 + \bar{x}^T \Phi_{2,k} \bar{x} + r_k^1 + 2(x_0^T \Phi_{01,k} x_1 + x_0^T \Phi_{02,k} \bar{x} + x_1^T \Phi_{12,k} \bar{x}).$$

By the first order condition, the minimizer in (33) satisfies

$$0 = (R + \alpha B^T \Phi_{1,t+1} B) u_t^1 + \alpha B^T \Phi_{12,t+1} B \bar{u}_t + \{ R_2^T + \alpha B^T [(\Phi_{1,t+1} + \Phi_{12,t+1}) D + \Phi_{01,t+1}^T B_0] \} u_t^0 + \alpha B^T [(\Phi_{1,t+1} + \Phi_{12,t+1}) G + \Phi_{01,t+1}^T A_0] x_0 + \alpha B^T \Phi_{1,t+1} A x_1 + \alpha B^T [\Phi_{1,t+1} F + \Phi_{01,t+1}^T F_0 + \Phi_{12,t+1} (A + F)] \bar{x}.$$

If  $R + \alpha B^T \Phi_{1,t+1} B$  is invertible, then

$$u_t^1 = - (R + \alpha B^T \Phi_{1,t+1} B)^{-1} \alpha B^T \{ [(\Phi_{1,t+1} + \Phi_{12,t+1}) G + \Phi_{01,t+1}^T A_0] x_0 + \Phi_{1,t+1} A x_1 + [\Phi_{1,t+1} F + \Phi_{01,t+1}^T F_0 + \Phi_{12,t+1} (A + F)] \bar{x} + \Phi_{12,t+1} B \bar{u}_t \} - (R + \alpha B^T \Phi_{1,t+1} B)^{-1}.$$

$$\{ R_2^T + \alpha B^T [(\Phi_{1,t+1} + \Phi_{12,t+1}) D + \Phi_{01,t+1}^T B_0] \} u_t^0. \quad (34)$$

By the *consistency condition*  $\bar{u}_t = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N u_t^i$ , with each  $u_t^i$  being a copy of  $u_t^1$  given by (34), we determine

$$\bar{u}_t = - [R + \alpha B^T (\Phi_{1,t+1} + \Phi_{12,t+1}) B]^{-1} \alpha B^T \{ [(\Phi_{1,t+1} + \Phi_{12,t+1}) G + \Phi_{01,t+1}^T A_0] x_0 + [(\Phi_{1,t+1} + \Phi_{12,t+1}) (A + F) + \Phi_{01,t+1}^T F_0] \bar{x} \} - [R + \alpha B^T (\Phi_{1,t+1} + \Phi_{12,t+1}) B]^{-1} \{ R_2^T + \alpha B^T [(\Phi_{1,t+1} + \Phi_{12,t+1}) D + \Phi_{01,t+1}^T B_0] \} u_t^0.$$

We write the above  $\bar{u}_t$  in the form

$$\bar{u}_t = \xi_{t+1}^0 X_t^0 + \xi_{t+1}^2 \bar{X}_t + \xi_{t+1}^3 u_t^0, \quad (35)$$

and further substitute (35) back into (34) to get

$$u_t^1 = \theta_{t+1}^0 X_t^0 + \theta_{t+1}^1 X_t^1 + \theta_{t+1}^2 \bar{X}_t + \theta_{t+1}^3 u_t^0, \quad (36)$$

where  $\xi_{t+1}^i$  and  $\theta_{t+1}^i$  are functions of  $\Phi_{i,t+1}$ . The control (36) is the best response of the minor player to  $u^0$  of the major player. (35) is the control mean field for given  $u^0$ .

### 5.2 Minimizer of the major player

Taking into account the best response (36), we solve the major player's minimization problem. By dynamic programming,

$$V_0(t, x_0, \bar{x}) = \min_{u^0} \{ |x_0 - \Gamma_0 \bar{x}|_{Q_0}^2 + |u_t^0|_{R_0}^2 + \alpha E[V_0(t+1, X_{t+1}^0, \bar{X}_{t+1})] \}_{(X_t^0, \bar{X}_t) = (x_0, \bar{x})}. \quad (37)$$

Assume that  $V_0$  takes the following form for  $k = t + 1$ ,

$$V_0(k, x_0, \bar{x}) = x_0^T \Phi_{0,k} x_0 + \bar{x}^T \Phi_{2,k} \bar{x} + 2x_0^T \Phi_{02,k} \bar{x} + r_k^0.$$

By the first order condition, the minimizer in (37) satisfies that

$$0 = R_0 u_t^0 + \alpha [B_0^T \Phi_{0,t+1}^0 + (B \xi_{t+1}^3 + D)^T \Phi_{02,t+1}^{0T}] (A_0 x_0 + B_0 u_t^0 + F_0 \bar{x}) + \alpha [B_0^T \Phi_{02,t+1}^0 + (B \xi_{t+1}^3 + D)^T \Phi_{02,t+1}^{0T}] [(A + F) \bar{x} + B (\xi_{t+1}^0 x_0 + \xi_{t+1}^2 \bar{x} + \xi_{t+1}^3 u_t^0) + D u_t^0 + G x_0].$$

If  $R_0 + \alpha [B_0^T \Phi_{0,t+1}^0 + (B \xi_{t+1}^3 + D)^T \Phi_{02,t+1}^{0T}] (B_0 + D_0)$  is invertible, we obtain from the first order condition that

$$u_t^0 = \beta_{t+1}^0 x_0 + \beta_{t+1}^2 \bar{x}, \quad (38)$$

where the  $\beta_{t+1}^i$  are functions of  $\Phi_{i,t+1}$  and  $\Phi_{i,t+1}^0$ .

### 5.3 Stackelberg equilibrium

We substitute (38) into (36) and (35) to obtain

$$u_t^1 = \hat{\theta}_{t+1}^0 x_0 + \hat{\theta}_{t+1}^1 x_1 + \hat{\theta}_{t+1}^2 \bar{x}, \quad (39)$$

$$\bar{u}_t = \hat{\xi}_{t+1}^0 x_0 + \hat{\xi}_{t+1}^2 \bar{x}, \quad (40)$$

where  $\hat{\theta}_{t+1}^i$  and  $\hat{\xi}_{t+1}^i$  are functions of  $\Phi_{i,t+1}$  and  $\Phi_{i,t+1}^0$ . The pair  $(u_t^0, u_t^1)$  in (38)-(39) is a Stackelberg equilibrium, and (40) is the control mean field.

We substitute the equilibrium  $(u_t^0, u_t^1, \bar{u}_t)$  given by (38)-(40) into (33) to obtain equations for  $\Phi_{i,t}$  and  $\Phi_{i,t}^0$ , which depend on  $\Phi_{i,t+1}$  and  $\Phi_{i,t+1}^0$ . We can solve for  $\Phi_{i,t}$  and  $\Phi_{i,t}^0$  backwards in time with zero terminal condition at  $T$ .

$$\Phi_{0,t} = [\Gamma_1]_Q^2 + [\theta_{t+1}^0]_R^2 + [\beta_{t+1}^0]_{R_1}^2 + \alpha [A_{t+1}^0]_{\Phi_{0,t+1}}^2 + \alpha [G_{t+1}]_{\Phi_{1,t+1}}^2 + \alpha [\bar{G}_{t+1}]_{\Phi_{2,t+1}}^2 + 2\alpha A_{t+1}^{0T} \Phi_{01,t+1} G_{t+1} + 2\alpha A_{t+1}^{0T} \Phi_{02,t+1} \bar{G}_{t+1} + 2\alpha G_{t+1}^T \Phi_{12,t+1} \bar{G}_{t+1},$$

$$\Phi_{1,t} = Q + [\hat{\theta}_{t+1}^1]_R^2 + \alpha [A_{t+1}]_{\Phi_{1,t+1}}^2,$$

$$\Phi_{2,t} = [\Gamma_2]_Q^2 + [\hat{\theta}_{t+1}^2]_R^2 + [\beta_{t+1}^2]_{R_1}^2 + \alpha [F_{t+1}]_{\Phi_{0,t+1}}^2 + \alpha [F_{t+1}]_{\Phi_{1,t+1}}^2 + \alpha [\bar{A}_{t+1}]_{\Phi_{2,t+1}}^2 + 2\alpha F_{t+1}^{0T} \Phi_{01,t+1} F_{t+1} + 2\alpha F_{t+1}^{0T} \Phi_{02,t+1} \bar{A}_{t+1} + 2\alpha F_{t+1}^T \Phi_{12,t+1} \bar{A}_{t+1},$$

$$\Phi_{01,t} = - \Gamma_1^T Q + \hat{\theta}_{t+1}^{0T} R \hat{\theta}_{t+1}^1 + \alpha G_{t+1}^T \Phi_{1,t+1} A_{t+1} + \alpha A_{t+1}^{0T} \Phi_{01,t+1} A_{t+1} + \alpha \bar{G}_{t+1}^T \Phi_{12,t+1} A_{t+1},$$

$$\Phi_{02,t} = \Gamma_1 Q \Gamma_2 + \hat{\theta}_{t+1}^{0T} R \hat{\theta}_{t+1}^2 + \beta_{t+1}^{0T} R_1 \beta_{t+1}^2 + \alpha A_{t+1}^{0T} \Phi_{0,t+1} F_{t+1}^0 + \alpha [G_{t+1}^T \Phi_{1,t+1} F_{t+1} + \bar{G}_{t+1}^T \Phi_{2,t+1} \bar{A}_{t+1}] + \alpha [A_{t+1}^{0T} \Phi_{01,t+1} F_{t+1} + G_{t+1}^T \Phi_{01,t+1}^T F_{t+1}] + \alpha [A_{t+1}^{0T} \Phi_{02,t+1} \bar{A}_{t+1} + \bar{G}_{t+1}^T \Phi_{02,t+1}^T F_{t+1}] + \alpha [G_{t+1}^T \Phi_{12,t+1} \bar{A}_{t+1} + \bar{G}_{t+1}^T \Phi_{12,t+1}^T F_{t+1}],$$

$$\begin{aligned} \Phi_{12,t} &= -Q\Gamma_2 + \widehat{\theta}_{t+1}^T R \widehat{\theta}_{t+1}^2 + \alpha A_{t+1}^T \Phi_{1,t+1} F_{t+1} \\ &\quad + \alpha [A_{t+1}^T \Phi_{01,t+1}^T F_{t+1}^0 + A_{t+1}^{0T} \Phi_{02,t+1} \overline{A}_{t+1}] \\ &\quad + \alpha [\overline{G}_{t+1}^T \Phi_{02,t+1}^T F_{t+1}^0 + A_{t+1}^T \Phi_{12,t+1} \overline{A}_{t+1}], \\ \Phi_{0,t}^0 &= [\Gamma_0]_{Q_0}^2 + [\beta_{t+1}^0]_{R_0}^2 + \alpha [A_{t+1}^0]_{\Phi_{0,t+1}^0}^2 + [\overline{G}_{t+1}]_{\Phi_{2,t+1}^0}^2 \\ &\quad + 2\alpha A_{t+1}^{0T} \Phi_{02,t+1}^0 \overline{G}_{t+1}, \\ \Phi_{2,t}^0 &= [\Gamma_0]_{Q_0}^2 + [\beta_{t+1}^2]_{R_0}^2 + \alpha [F_{t+1}^0]_{\Phi_{0,t+1}^0}^2 + [\overline{A}_{t+1}]_{\Phi_{2,t+1}^0}^2 \\ &\quad + 2\alpha A_{t+1}^{0T} \Phi_{02,t+1}^0 \overline{A}_{t+1}, \\ \Phi_{02,t}^0 &= -Q_0 \Gamma_0 + \beta_{t+1}^{0T} R_0 \beta_{t+1}^0 + \alpha A_{t+1}^{0T} \Phi_{0,t+1}^0 F_{t+1}^0 \\ &\quad + \alpha [\overline{G}_{t+1}^T \Phi_{02,t+1}^0 \overline{A}_{t+1} + A_{t+1}^{0T} \Phi_{02,t+1}^0 \overline{A}_{t+1}] \\ &\quad + \alpha \overline{G}_{t+1}^T \Phi_{02,t+1}^{0T} F_{t+1}^0. \end{aligned}$$

In the above equations, the matrices  $A_{t+1}^0$ ,  $F_{t+1}^0$ ,  $A_{t+1}$ ,  $F_{t+1}$ ,  $G_{t+1}$ ,  $\overline{A}_{t+1}$  and  $\overline{G}_{t+1}$  are defined as

$$\begin{aligned} A_{t+1}^0 &= A_0 + B_0 \beta_{t+1}^0, \quad F_{t+1}^0 = F_0 + B_0 \beta_{t+1}^2, \\ A_{t+1} &= A + B \widehat{\theta}_{t+1}^1, \quad F_{t+1} = F + B \widehat{\theta}_{t+1}^2 + D \beta_{t+1}^2, \\ G_{t+1} &= G + B \widehat{\theta}_{t+1}^0 + D \beta_{t+1}^0, \\ \overline{A}_{t+1} &= A + F + B \widehat{\xi}_{t+1}^2 + D \beta_{t+1}^2, \\ \overline{G}_{t+1} &= G + B \widehat{\xi}_{t+1}^0 + D \beta_{t+1}^0. \end{aligned}$$

*Remark 3.* The continuous-time LQ model needs the control-coupling term  $u^{0T} R_2 u^1$  in (18) so that the best response of the minor player explicitly involves  $u^0$ , which enables the major player's leadership. In the discrete-time case, leadership can be generated by dynamic coupling alone without control-coupling.

## 6. CONCLUDING REMARKS

For mean field Stackelberg games with a major player, we apply dynamic programming to find feedback equilibrium strategies. For future work, it is of interest to analyze the performance of the decentralized strategies applied by a finite population.

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