

# OPTIMAL EXERCISE DECISION OF AMERICAN OPTIONS UNDER MODEL UNCERTAINTY

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ABSTRACT. Given the marginal distribution information of the underlying asset price at two future times  $T_1$  and  $T_2$ , we consider the problem of determining a model-free upper bound on the price of a class of American options that must be exercised at either  $T_1$  or  $T_2$ . The model uncertainty consistent with the given marginal information is described as the martingale optimal transport problem. We show that if the American option payoff satisfies a suitable convexity condition, then any option exercise scheme associated with any market model that jointly maximizes the expected option payoff must be nonrandomized.

*Keywords:* Robust finance, American option, Hedging, Martingale, Optimal transport, Duality, Dual attainment, Infinite-dimensional linear programming  
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## 1. INTRODUCTION

This paper was mainly inspired by Hobson and Norgilas [18], Aksamit, Deng, Obłój and Tan [1], as well as Beiglböck and Juillet [8] and Beiglböck, Nutz and Touzi [9]. A related problem in continuous time setup was studied in Bayraktar, Cox and Stoev [2]. We consider two future times  $0 < T_1 < T_2$  and an asset price process  $(X, Y)$ , where  $X, Y$  represents the asset price at time  $T_1, T_2$ , respectively. Let  $\mathcal{P}(\mathcal{X})$  denote the set of all probability measures/distributions over a set  $\mathcal{X}$  with finite first moment. Let  $\mu, \nu \in \mathcal{P}(\mathbb{R})$  be probability measures in convex order:

$$\mu \preceq_c \nu \text{ if } \mu(f) \leq \nu(f) \text{ for every convex function } f \text{ on } \mathbb{R},$$

where  $\mu(f) := \mathbb{E}_\mu[f(X)] = \int f(x)\mu(dx)$ . We consider market models that are defined by the following set of martingale transports from  $\mu$  to  $\nu$ :

$$\mathcal{M}(\mu, \nu) = \{\pi \in \mathcal{P}(\mathbb{R}^2) \mid \pi = \text{Law}(X, Y), \mathbb{E}_\pi[Y|X] = X, \text{Law}(X) = \mu, \text{Law}(Y) = \nu\}.$$

In finance, each  $\pi \in \mathcal{M}(\mu, \nu)$  represents a feasible joint law of the price  $(X, Y)$  given the marginal information  $\mu, \nu$  in the (two-period) market, under which  $(X, Y)$  is a martingale, written as  $\mathbb{E}_\pi[Y|X] = X$ . It is well known that the condition  $\mu \preceq_c \nu$  is equivalent to  $\mathcal{M}(\mu, \nu) \neq \emptyset$ . We refer to [10, 11, 13, 14] for further background.

We consider the cost function which describes an American option payoff

$$(1.1) \quad c = (c_1, c_2) = (c_1(x), c_2(x, y)), \quad c_1, c_2 \in \mathbb{R},$$

such that if an obligee (option holder) selects  $c_1$ , she receives the payout  $c_1(X)$ , otherwise she receives the payout  $c_2(X, Y)$ . Thus, in the former case, her payout is determined at time 1, whereas it is determined at time 2 in the latter. We assume she can make this choice conditional on the price  $X = x$ , and that she can also randomize (or split) her choice, represented by a Borel function  $s : \mathbb{R} \rightarrow [0, 1]$ . This means that given  $X = x$ , she exercises  $c_1$  with probability (or proportion)  $s(x)$ , otherwise  $c_2$  with probability  $1 - s(x)$ . Given a function  $s : \mathbb{R} \rightarrow \mathbb{R}$  and a measure  $\mu$  on  $\mathbb{R}$ , let the measure  $s\mu$  be given by  $s\mu(B) = \int_B s(x)\mu(dx)$ . Since  $\mu$  is fixed, the choice of a randomization  $s$  is equivalent to the choice of  $0 \leq \mu_1 \leq \mu$ ,<sup>1</sup> such that with  $\mu_2 := \mu - \mu_1$ ,  $s_1 := s$ ,  $s_2 := 1 - s$  equals the Radon–Nikodym derivative  $\frac{d\mu_1}{d\mu}, \frac{d\mu_2}{d\mu}$   $\mu$ -a.s., respectively. This leads us to consider the optimization problem

$$(1.2) \quad P_c := \sup_{\pi \in \mathcal{M}(\mu, \nu)} \sup_{\mu_1 \leq \mu} \mathbb{E}_{\gamma_1}[c_1] + \mathbb{E}_{\gamma_2}[c_2],$$

where for a given  $\pi = \pi_x \otimes \mu \in \mathcal{M}(\mu, \nu)$ ,<sup>2</sup> we define  $\gamma_l = \pi_x \otimes \mu_l$ ,  $l = 1, 2$ , such that  $\gamma_1 + \gamma_2 = \pi$  and that  $\gamma_1$  and  $\gamma_2$  share the same kernel  $\{\pi_x\}_x$  inherited from  $\pi$ .

In view of the obligor (the person responsible for the payment of the option), a solution  $(\pi, \mu_1)$  to (1.2) represents a worst-possible market scenario  $\pi$  combined with the option exercise scheme  $\mu_1$ , yielding the maximum expected payout  $P_c$ .

We will assume the following regularity condition on  $c$  throughout the paper.

**[A]** Throughout the paper, we assume that  $c_1, c_2$  are continuous,  $\mu \preceq_c \nu$ , and that the marginals  $\mu, \nu$  satisfy the following condition: there exist continuous functions

<sup>1</sup>All measures/distributions in this paper are assumed to be non-negative.

<sup>2</sup>Any  $\pi = \text{Law}(X, Y) \in \mathcal{P}(\mathbb{R}^2)$ , representing the joint law of the random variables  $X$  and  $Y$ , can be written as  $\pi = \pi_x \otimes \text{Law}(Y|X)$ , where  $\pi_x \in \mathcal{P}(\mathbb{R})$  is called a kernel of  $\pi$  with respect to  $\text{Law}(X)$ .  $\pi_x$  represents the conditional distribution of  $Y$  given  $X = x$ , i.e.,  $\pi_x(B) = \mathcal{P}(Y \in B | X = x)$  for all Borel set  $B \subseteq \mathbb{R}$ . Note that  $\pi = \pi_x \otimes \mu \in \mathcal{M}(\mu, \nu)$  iff  $\int y \pi_x(dy) = x$   $\mu$ -a.e.  $x$ .

$v \in L^1(\mu)$ ,  $w \in L^1(\nu)$  such that  $|c_1| + |c_2| \leq v(x) + w(y)$ . Note that this implies  $|\sum_l \mathbb{E}_{\gamma_l}[c_l]| \leq \sum_l \mathbb{E}_{\gamma_l}[|c_l|] \leq \sum_l \mathbb{E}_{\pi}[|c_l|] \leq \mu(v) + \nu(w) < \infty$  for any  $\pi \in \mathcal{M}(\mu, \nu)$ .

This in turn implies that the problem (1.2) is attained (i.e., admits an optimizer) by a standard argument in the calculus of variations [22].

[18] considered a specific cost called an American put, whose payoff is given by

$$(1.3) \quad c_1(x) = (K_1 - x)^+, \quad c_2(x, y) = c_2(y) = (K_2 - y)^+, \quad K_1 > K_2,$$

and considered those option exercise schemes which are *pure*, or *non-randomized*; that is, [18] assumed that the obligee can only choose a Borel set  $B \subseteq \mathbb{R}$  in which she selects  $c_1$  if  $x \in B$  and  $c_2$  otherwise. In terms of  $\mu_1$ , notice that this is equivalent to the statement that  $\mu_1$  and  $\mu_2$  are mutually disjoint, written as  $\mu_1 \perp \mu_2$  (while  $\mu_1 + \mu_2 = \mu$ ). In other words, [18] assumed that  $\mu_1, \mu_2$  must saturate  $\mu$  on their respective supports. In addition, [18] assumed that  $\mu$  is continuous, i.e., has no atoms. Under these assumptions, [18] showed that an optimal market model  $\pi$  for the problem (1.2) is given by the *left-curtain coupling* (see [8, 15, 18] for more details about this interesting martingale transport) along with an optimal exercise strategy  $B$ , and furthermore, the cheapest superhedge can be derived.

Now we would like to shift our focus and ask, “Under what conditions must the optimal option exercise be pure?” That is, when will an optimal  $\mu_1$  saturate  $\mu$ , or equivalently, achieve  $\mu_1 \perp \mu_2$ ? Note that the problem (1.2) can be rewritten as

$$(1.4) \quad P_c = \sup_{\mu_1 \leq \mu} P_c(\mu_1), \quad \text{where } P_c(\mu_1) := \sup_{\pi \in \mathcal{M}(\mu, \nu)} \mathbb{E}_{\gamma_1}[c_1] + \mathbb{E}_{\gamma_2}[c_2],$$

where  $\gamma_l = \pi_x \otimes \mu_l$ ,  $l = 1, 2$ . As a result, we break down the problem (1.2), which has a non-convex domain,<sup>3</sup> into subproblems  $P_c(\mu_1)$  in which  $(\mu_1, \mu_2)$  is fixed, and as a result, has a convex subdomain. We now present our main result.

**Theorem 1.1.** *Assume [A]. Suppose  $y \mapsto c_2(x, y)$  is strictly convex and  $c_1(x) \neq c_2(x, x)$  for  $\mu$ -a.e.  $x$ , and  $\nu$  is absolutely continuous with respect to the Lebesgue measure. Then every solution  $(\pi, \mu_1)$  to the problem (1.4) satisfies  $\mu_1 \perp \mu - \mu_1$ .*

<sup>3</sup>A feasible pair  $(\pi, \mu_1)$  in (1.2) can be seen equivalent to the corresponding  $(\pi_1, \pi_2)$ . Now even if  $(\pi_1, \pi_2), (\pi'_1, \pi'_2)$  are feasible (i.e., sharing the same kernel respectively), the convex combination  $(\frac{\pi_1 + \pi'_1}{2}, \frac{\pi_2 + \pi'_2}{2})$  may not share the same kernel thus infeasible, unless  $\mu_1 = \mu'_1$  and  $\mu_2 = \mu'_2$ .

We note that the condition  $c_1(x) > c_2(x, x)$  is natural because, if  $c_1(x) \leq c_2(x, x)$  and  $c_2$  is convex in  $y$ , it is always optimal to choose  $c_2(x, y)$  by Jensen's inequality  $c_2(x, x) \leq \int c_2(x, y)\pi_x(dy)$ . Theorem 1.1 says that in this case, every optimal exercise, or stopping, is nonrandomized. Evidently, the problem (1.2) can be viewed as an optimal stopping problem, in which the option holder either stops at time 1 and receives the sure reward  $c_1(x)$ , or goes and receives the reward  $c_2(x, y)$  (which is stochastic at time 1) at time 2. This naturally places the theorem in the context of the vast literature on the Skorokhod embedding problem [7, 16, 21], with the key difference that we now face uncertainty in the family of models  $\mathcal{M}(\mu, \nu)$ . Such model uncertainty was also considered in [2, 12] in continuous time setup. For more results on American options and their robust hedging, we refer to [4–6].

We also note that in the optimal transport literature, the absolute continuity of  $\mu$  is typically assumed in order to derive non-randomizing solutions, known as Monge solutions. Continuity of  $\mu$  was also assumed in [18]. In contrast, Theorem 1.1 assumes the absolute continuity of  $\nu$ , while making no assumptions about  $\mu$ .

The remainder of the paper is structured as follows. The theorem will be proved utilizing three propositions, two of which are related to duality (no duality gap), and one of which is a dual attainment result. They will be discussed in Section 2. Section 3 then presents proofs of the results.

## 2. DUALITY

In this section, we consider cost functions more general than (1.1), such as

$$(2.1) \quad \vec{c} = (c_1, c_2, \dots, c_L), \quad c_l = c_l(x, y) \in \mathbb{R}, \quad l = 1, 2, \dots, L.$$

Throughout this section, we assume the following.

**[A']**  $c_l$  are continuous for all  $l$ ,  $\mu \preceq_c \nu$ , and  $\sum_{l=1}^L |c_l(x, y)| \leq v(x) + w(y)$  for some continuous functions  $v \in L^1(\mu)$ ,  $w \in L^1(\nu)$ .

Let  $\vec{\mu} = (\mu_1, \dots, \mu_L)$  satisfy  $\sum_{l=1}^L \mu_l = \mu$ . We can generalize the subproblem in (1.4) into the following

$$(2.2) \quad P_c(\vec{\mu}) := \sup_{\pi \in \mathcal{M}(\mu, \nu)} \sum_{l=1}^L \mathbb{E}_{\gamma_l}[c_l], \quad \text{where } \gamma_l = \pi_x \otimes \mu_l.$$

Financially, the option holder has the right of selecting one of the payouts  $c_l$ , which can be randomized depending on  $x$ , as described by the probability vector  $(\frac{d\mu_l}{d\mu}(x))$ .

The problem (2.2) has a natural dual problem. To describe, let  $s_l : \mathbb{R} \rightarrow [0, 1]$ ,  $\sum_{l=1}^L s_l(x) = 1$ , be a version of the densities  $\frac{d\mu_l}{d\mu}$ . Then (2.2) can be rewritten as

$$(2.3) \quad P_c(\vec{\mu}) = \sup_{\pi \in \mathcal{M}(\mu, \nu)} \mathbb{E}_\pi[\sum_l s_l c_l],$$

where  $s_l c_l(x, y) = s_l(x) c_l(x, y)$ . Regarding  $\sum_l s_l c_l$  as the cost function, a well known dual problem of (2.3) is given by

$$(2.4) \quad \inf_{(\varphi, \psi, \theta)} \mu(\varphi) + \nu(\psi),$$

where  $\varphi \in C(\mathbb{R}) \cap L^1(\mu)$ ,  $\psi \in C(\mathbb{R}) \cap L^1(\nu)$ ,  $\theta \in C_b(\mathbb{R})$ , that satisfies  $\sum_l s_l c_l(x, y) \leq \varphi(x) + \psi(y) + \theta(x)(y - x)$ , where  $C(\mathcal{X})$ ,  $C_b(\mathcal{X})$  denotes the space of all continuous (or continuous and bounded) functions on  $\mathcal{X}$ . Then it is known that the values (2.3) and (2.4) coincide (see [8, 9].) Nonetheless, the dual formulation (2.4) turns out to be not so helpful for our needs, prompting us to consider the following alternative. Define  $\Psi_c$  to be the space of functions  $(\vec{\varphi}, \psi, \vec{\theta}) = (\varphi_1, \dots, \varphi_L, \psi, \theta_1, \dots, \theta_L)$  such that  $\varphi_l \in C(\mathbb{R}) \cap L^1(\mu)$ ,  $\psi \in C(\mathbb{R}) \cap L^1(\nu)$ ,  $\theta_l \in C_b(\mathbb{R})$ , and that

$$(2.5) \quad c_l(x, y) \leq \varphi_l(x) + \psi(y) + \theta_l(x)(y - x) \quad \text{for all } l = 1, \dots, L \text{ and } (x, y) \in \mathbb{R}^2.$$

We then consider the following problem

$$(2.6) \quad D_c(\vec{\mu}) := \inf_{(\vec{\varphi}, \psi, \vec{\theta}) \in \Psi_c} \nu(\psi) + \sum_l \mu_l(\varphi_l).$$

The inequality  $P_c(\vec{\mu}) \leq D_c(\vec{\mu})$  is immediate by integrating (2.5) by  $\gamma_l$  and summing up in  $l$ . We will show the following duality result for the problem (2.2).

**Proposition 2.1.** *Assume [A']. Then  $P_c(\vec{\mu}) = D_c(\vec{\mu})$ .*

We turn to the second duality result. As noted, the domain of the problem (1.2), in terms of the variable  $(\gamma_1, \gamma_2)$ , is nonconvex. This leads us to consider a relaxed problem for (1.2); see also [1] for related results. Let  $\mathcal{M} := \cup_{\mu \preceq_c \nu} \mathcal{M}(\mu, \nu)$ , that is,  $\mathcal{M}$  is the set of all martingale transports between some probability marginals in convex order, hence  $\mathcal{M} \subseteq \mathcal{P}(\mathbb{R}^2)$ . Let  $\overline{\mathcal{M}}$  be the set of all martingale transports with arbitrary nonnegative finite total mass, that is,  $\gamma \in \overline{\mathcal{M}}$  if  $\gamma \equiv 0$  or  $\gamma/||\gamma|| \in \mathcal{M}$  where  $||\gamma|| = \int_{\mathbb{R}^2} \gamma(dx, dy) \in (0, \infty)$  denotes the total mass. Define

$$\mathcal{M}_L(\mu, \nu) := \left\{ \vec{\gamma} = (\gamma_1, \dots, \gamma_L) \left| \sum_{l=1}^L \gamma_l \in \mathcal{M}(\mu, \nu) \text{ and } \gamma_l \in \overline{\mathcal{M}} \text{ for all } l = 1, \dots, L. \right. \right\}$$

$\mathcal{M}_L(\mu, \nu)$  is clearly convex. Now we define the relaxed problem

$$(2.7) \quad \overline{P}_c := \sup_{\vec{\gamma} \in \mathcal{M}_L(\mu, \nu)} \sum_{l=1}^L \mathbb{E}_{\gamma_l}[c_l].$$

The difference is that in (1.2) (with the generalized cost (2.1)),  $\{\gamma_l\}_l$  are assumed to have the same kernel  $\pi_x$  inherited from a model  $\pi \in \mathcal{M}(\mu, \nu)$ , whereas in (2.7), this restriction is relaxed. Both problems satisfy the condition  $\sum_l \gamma_l \in \mathcal{M}(\mu, \nu)$ . Hence,  $P_c \leq \overline{P}_c$ . We will show  $P_c = \overline{P}_c$ . This can be best seen via duality associated to (2.7). Define  $\overline{\Psi}_c$  to be the space of functions  $(\varphi, \psi, \vec{\theta}) = (\varphi, \psi, \theta_1, \dots, \theta_L)$  such that  $\varphi \in C(\mathbb{R}) \cap L^1(\mu)$ ,  $\psi \in C(\mathbb{R}) \cap L^1(\nu)$ ,  $\theta_l \in C_b(\mathbb{R})$ , satisfying

$$(2.8) \quad c_l(x, y) \leq \varphi(x) + \psi(y) + \theta_l(x)(y - x) \quad \text{for all } l = 1, \dots, L \text{ and } (x, y) \in \mathbb{R}^2.$$

The difference is that in (2.5) the functions  $\varphi_l$  can be distinct, whereas in (2.8), there is only one  $\varphi$ . The dual problem to (2.7) is now given by

$$(2.9) \quad \overline{D}_c := \inf_{(\varphi, \psi, \vec{\theta}) \in \overline{\Psi}_c} \mu(\varphi) + \nu(\psi).$$

The second duality result is the following; see also [1].

**Proposition 2.2.** *Assume [A']. Then  $P_c = \overline{P}_c = \overline{D}_c$ .*

For the financial meaning of the dual problems in terms of American option superhedging, we refer to [1, 3–6, 17, 18, 20]. The final element required to prove Theorem 1.1 is the dual attainment result, which asserts that there is an appropriate solution to the dual problem (2.9). For  $\xi \in \mathcal{P}(\mathbb{R})$ , its potential function is defined by  $u_\xi(x) := \int |x - y| d\xi(y)$ . Then we say that a pair of probabilities  $(\mu, \nu)$  in convex order is irreducible if the set  $I := \{x \in \mathbb{R} \mid u_\mu(x) < u_\nu(x)\}$  is a connected (open) interval containing the full mass of  $\mu$ , i.e.,  $\mu(I) = \mu(\mathbb{R})$ .

**Proposition 2.3.** *Assume [A'] and suppose  $(\mu, \nu)$  is irreducible. Then there exists a dual optimizer  $(\varphi, \psi, \vec{\theta})$ ,  $\varphi, \psi : \mathbb{R} \rightarrow \mathbb{R} \cup \{+\infty\}$ ,  $\theta_l : \mathbb{R} \rightarrow \mathbb{R}$ , that satisfies (2.8) tightly in the following pathwise sense (but needs not be in  $\overline{\Psi}_c$ ):*

$$(2.10) \quad c_l(x, y) = \varphi(x) + \psi(y) + \theta_l(x)(y - x) \quad \gamma_l - \text{a.e.}, \quad \text{for all } l = 1, \dots, L$$

for every solution  $\vec{\gamma} = (\gamma_1, \dots, \gamma_L)$  to the problem (2.7), and hence, (1.2).

We emphasize that  $(\varphi, \psi, \vec{\theta})$  may not be in  $\overline{\Psi}_c$  but are only measurable, with  $\varphi, \psi$  real-valued  $\mu, \nu$ -a.s., respectively. They need not be integrable nor continuous.

## 3. PROOFS

*Proof of Proposition 2.1.* Let  $\mathcal{N}$  be the set of all nonnegative measures on  $\mathbb{R}^2$  (that do not need to be martingales.) For  $\gamma \in \mathcal{N}$ , let  $\gamma^X, \gamma^Y$  denote its marginal on the  $x, y$ -coordinate respectively. Below,  $\gamma_l = \pi_x \otimes \mu_l$ ,  $s_l = s_l(x) \in C_b(\mathbb{R})$  is nonnegative, and  $(\vec{\varphi}, \psi, \vec{\theta}) \in \Psi_c$ . We claim that the following equalities hold:

$$\begin{aligned}
P_c(\vec{\mu}) &= \sup_{\pi \in \mathcal{M}(\mu, \nu)} \sum_{l=1}^L \gamma_l(c_l) \\
&= \sup_{\pi \in \mathcal{N}} \sup_{s_1, \dots, s_L} \inf_{(\vec{\varphi}, \psi, \vec{\theta})} \sum_l s_l \pi(c_l) + \sum_l (\mu_l - (s_l \pi)^X)(\varphi_l) + (\nu - \sum_l (s_l \pi)^Y)(\psi) - \sum_l s_l \pi(\theta_l(x)(y-x)) \\
&= \sup_{\pi \in \mathcal{N}} \inf_{(\vec{\varphi}, \psi, \vec{\theta})} \sup_{s_1, \dots, s_L} \sum_l \mu_l(\varphi_l) + \nu(\psi) + \sum_l s_l \pi(c_l(x, y) - \varphi_l(x) - \psi(y) - \theta_l(x)(y-x)) \\
&= \sup_{\pi \in \mathcal{N}} \inf_{c_l(x, y) \leq \varphi_l(x) + \psi(y) + \theta_l(x)(y-x) \forall l \text{ on } \text{spt}(\pi)} \sum_l \mu_l(\varphi_l) + \nu(\psi) \\
&= \inf_{c_l(x, y) \leq \varphi_l(x) + \psi(y) + \theta_l(x)(y-x) \forall l} \sum_l \mu_l(\varphi_l) + \nu(\psi) = D_c(\vec{\mu}).
\end{aligned}$$

The derivation of the equalities is fairly standard: the second equality holds because the infimum achieves  $-\infty$  as soon as  $(s_l \pi)^X \neq \mu_l$ ,  $\sum_l (s_l \pi)^Y \neq \nu$ , or  $s_l \pi \neq \overline{\mathcal{M}}$ , thus, the collection of measures  $(s_l \pi)_l$  must observe the constraint imposed on  $(\gamma_l)_l$  in the problem  $P_c(\vec{\mu})$ . The third equality is based on a standard minimax theorem, which asserts that the equality holds when the sup and inf are swapped. Because the objective function is bilinear, i.e., linear in each variable  $((s_l)_l$  and  $(\vec{\varphi}, \psi, \vec{\theta})$ ), the minimax theorem holds in this case and we omit the detail. The fourth equality is because, if  $c_l(x, y) - \varphi_l(x) - \psi(y) - \theta_l(x)(y-x) > 0$  for some  $(x, y) \in \text{spt}(\pi)$ , one can select  $s_l$  such that the last supremum in the third line achieves  $+\infty$ , which is not helpful to achieve the middle infimum. Finally, the supremum in the fourth line is obviously achieved for those  $\pi$  with  $\text{spt}(\pi) = \mathbb{R}^2$ , completing the proof.  $\square$

*Proof of Proposition 2.2.* Let  $(\varphi, \psi, \vec{\theta}) \in \overline{\Psi}_c$ . The following equalities hold:

$$\begin{aligned}
\overline{P}_c &= \sup_{\vec{\gamma} \in \mathcal{M}_L(\mu, \nu)} \sum_{l=1}^L \mathbb{E}_{\gamma_l}[c_l] \\
&= \sup_{\gamma_l \in \mathcal{N} \forall l} \inf_{(\varphi, \psi, \vec{\theta})} \sum_l \gamma_l(c_l) + (\mu - \sum_l \gamma_l^X)(\varphi) + (\nu - \sum_l \gamma_l^Y)(\psi) - \sum_l \gamma_l(\theta_l(x)(y-x)) \\
&= \inf_{(\varphi, \psi, \vec{\theta})} \sup_{\gamma_l \in \mathcal{N} \forall l} \mu(\varphi) + \nu(\psi) + \sum_l \gamma_l(c_l(x, y) - \varphi(x) - \psi(y) - \theta_l(x)(y-x)) \\
&= \inf_{c_l(x, y) \leq \varphi(x) + \psi(y) + \theta_l(x)(y-x) \forall l} \mu(\varphi) + \nu(\psi) = \overline{D}_c.
\end{aligned}$$

The derivation is simpler than that of Proposition 2.1 and we omit the detail. Let  $\Xi = \{\vec{\mu} = (\mu_1, \dots, \mu_L) \mid \mu_l \text{ is a nonnegative measure on } \mathbb{R}, \text{ and } \sum_l \mu_l = \mu\}$ . Below,  $\bar{\varphi} := \max(\varphi_1, \varphi_2, \dots, \varphi_L)$ . Now to show  $P_c = \bar{P}_c$ , we can proceed

$$\begin{aligned}
P_c &= \sup_{\vec{\mu} \in \Xi} P_c(\vec{\mu}) = \sup_{\vec{\mu} \in \Xi} D_c(\vec{\mu}) \\
&= \sup_{\vec{\mu} \in \Xi} \inf_{(\vec{\varphi}, \psi, \bar{\theta}) \in \Psi_c} \nu(\psi) + \sum_l \mu_l(\varphi_l) \\
&= \inf_{(\vec{\varphi}, \psi, \bar{\theta}) \in \Psi_c} \sup_{\vec{\mu} \in \Xi} \nu(\psi) + \sum_l \mu_l(\varphi_l) \\
&= \inf_{(\vec{\varphi}, \psi, \bar{\theta}) \in \Psi_c} \nu(\psi) + \mu(\bar{\varphi}) \\
&= \inf_{(\varphi, \psi, \bar{\theta}) \in \bar{\Psi}_c} \nu(\psi) + \mu(\varphi) = \bar{D}_c = \bar{P}_c,
\end{aligned}$$

where it is clear that  $\sup_{\vec{\mu} \in \Xi} \sum_l \mu_l(\varphi_l) = \mu(\bar{\varphi})$ , so is the equality in the last line.  $\square$

*Proof of Proposition 2.3.* The proof mostly consist of extending the ideas in [8, 9] to the vectorial cost (2.1). We will follow the five steps illustrated in [19], thereby omitting some details here but referring to the corresponding steps in [19].

**Step 1.**  $\sum_{l=1}^L |c_l(x, y)| \leq v(x) + w(y)$  for some continuous functions  $v \in L^1(\mu)$ ,  $w \in L^1(\nu)$ . A dual optimizer exists for  $\vec{c}$  iff so does for  $\tilde{c} := (c_l(x, y) + v(x) + w(y))_l$ . Thus by replacing  $\vec{c} = (c_1, \dots, c_L)$  with  $\tilde{c}$ , from now on we assume  $c_l \geq 0$  for all  $l$ .

As  $\bar{P}_c = \bar{D}_c \in \mathbb{R}$ , we can find an approximating dual optimizer  $(\varphi_n, \psi_n, \theta_{l,n}) \in \bar{\Psi}_c$ ,  $n \in \mathbb{N}$ , such that the following duality holds (for all  $l = 1, \dots, L$ ):

$$(3.1) \quad \varphi_n(x) + \psi_n(y) + \theta_{l,n}(x)(y - x) \geq c_l(x, y) \geq 0,$$

$$(3.2) \quad \mu(\varphi_n) + \nu(\psi_n) \searrow \bar{P}_c \text{ as } n \rightarrow \infty.$$

Define  $f_n = -\varphi_n$ ,  $h_{l,n} = -\theta_{l,n}$ , so that (3.1) becomes

$$(3.3) \quad f_n(x) + h_{l,n}(x)(y - x) \leq \psi_n(y) - c_l(x, y) \leq \psi_n(y).$$

Define the convex functions

$$(3.4) \quad \chi_{l,n}(y) := \sup_{x \in \mathbb{R}} f_n(x) + h_{l,n}(x)(y - x), \quad \chi_n := \sup_{l=1, \dots, L} \chi_{l,n}.$$

Notice  $\chi_{l,n}(y) \geq f_n(y) + h_{l,n}(y)(y - y) = f_n(y)$  for all  $y \in \mathbb{R}$ . Hence,

$$(3.5) \quad f_n \leq \chi_n \leq \psi_n \text{ for all } n.$$



By (3.2), this yields the uniform integral bound

$$(3.6) \quad \int \chi_n d(\nu - \mu) \leq \nu(\psi_n) - \mu(f_n) \leq C \quad \text{for all } l = 1, \dots, L \text{ and } n \in \mathbb{N}.$$

Using (3.6) and the assumption that  $(\mu, \nu)$  is irreducible, a local uniform boundness of  $\{\chi_n\}_n$  can be obtained (cf. Step 1 in the proof of [19, Theorem 1.2]): there exists an increasing sequence of compact intervals  $J_k := [c_k, d_k]$  and constants  $M_k \geq 0$  for each  $k \in \mathbb{N}$ , such that  $\cup_{k=1}^{\infty} J_k = J$ , and

$$(3.7) \quad 0 \leq \sup_n \chi_n \leq M_k \quad \text{in } J_k.$$

**Step 2.** Given any approximating dual optimizer  $(\varphi_n, \psi_n, \theta_{l,n})$  satisfying (3.2), (3.3), the goal is to suitably modify it and deduce pointwise convergence of  $\varphi_n, \psi_n$  to some functions  $\varphi, \psi$   $\mu, \nu$ -a.s. as  $n \rightarrow \infty$ , respectively, where  $\varphi, \psi \in \mathbb{R} \cup \{+\infty\}$  is  $\mu, \nu$ -a.s. finite. From convexity of  $\chi_n$  with  $\mu \preceq_c \nu$ , we deduce, for all  $n$ ,

$$(3.8) \quad C \geq \nu(\psi_n) - \mu(f_n) \geq \nu(\chi_n) - \mu(f_n) \geq \mu(\chi_n) - \mu(f_n) = \|\chi_n - f_n\|_{L^1(\mu)},$$

Meanwhile, (3.3) gives  $f_n(x) + h_{l,n}(x)(y - x) - \psi_n(y) \leq -c_l(x, y) \leq 0$ , hence

$$f_n(x) + h_{l,n}(x)(y - x) - \psi_n(y) \leq \chi_n(y) - \psi_n(y) \leq 0.$$

Integrating by any  $\pi \in \mathcal{M}(\mu, \nu)$  implies

$$(3.9) \quad \|\psi_n - \chi_n\|_{L^1(\nu)} \leq \nu(\psi_n) - \mu(f_n) \leq C \quad \text{for all } n.$$

These uniform  $L^1$  bounds, combined with the local uniform bound (3.7) and Komlós compactness theorem, can imply the desired almost sure convergence of  $\{\varphi_n\}$  and  $\{\psi_n\}$  as presented in [9] and in Step 2 in the proof of [19, Theorem 1.2], thus we omit the detail here. Also, by following Step 3 in the same proof, one can deduce the following pointwise convergence of  $\chi_n$  to a convex function  $\chi$

$$(3.10) \quad \lim_{n \rightarrow \infty} \chi_n(y) = \chi(y) \in \mathbb{R} \quad \text{for every } y \in J.$$

**Step 3.** We have obtained the almost sure limit functions  $\varphi, \psi$ , with  $f := -\varphi$ . We may define  $\varphi := +\infty$  on a  $\mu$ -null set which includes  $\mathbb{R} \setminus I$ , and  $\psi := +\infty$  on a  $\nu$ -null set which includes  $\mathbb{R} \setminus J$ , so that they are defined everywhere on  $\mathbb{R}$ . We will show there exists a function  $\theta_l : \mathbb{R} \rightarrow \mathbb{R}$ , with  $h_l := -\theta_l$ ,  $l = 1, \dots, L$ , such that

$$(3.11) \quad \varphi(x) + \psi(y) + \theta_l(x)(y - x) \geq c_l(x, y).$$

For any function  $f : \mathbb{R} \rightarrow \mathbb{R} \cup \{+\infty\}$  which is bounded below by an affine function, let  $\text{conv}[f] : \mathbb{R} \rightarrow \mathbb{R} \cup \{+\infty\}$  denote the lower semi-continuous convex envelope of  $f$ , that is the supremum of all affine functions  $\lambda$  satisfying  $\lambda \leq f$  (If there is no such  $\lambda$ , let  $\text{conv}[f] \equiv -\infty$ .) Set  $H_{l,n}(x, y) := \text{conv}[\psi_n(\cdot) - c_l(x, \cdot)](y)$ . By (3.3),

$$(3.12) \quad f_n(x) + h_{l,n}(x)(y - x) \leq H_{l,n}(x, y) \leq \psi_n(y) - c_l(x, y),$$

because the left hand side is affine in  $y$ . Letting  $y = x$  gives  $f_n(x) \leq H_{l,n}(x, x)$ .

Next, since the lim sup of convex functions is convex, we have

$$\begin{aligned} \limsup_{n \rightarrow \infty} H_{l,n}(x, y) &\leq \text{conv}[\limsup_{n \rightarrow \infty} (\psi_n(\cdot) - c_l(x, \cdot))](y) \\ &\leq \text{conv}[\psi(\cdot) - c_l(x, \cdot)](y) =: H_l(x, y). \end{aligned}$$

Then by the convergence  $f_n \rightarrow f$  and the definition of  $H_l(x, y)$ , we get

$$f(x) \leq H_l(x, x), \text{ and } H_l(x, y) \leq \psi(y) - c_l(x, y).$$

Set  $A := \{x \in I \mid \lim_{n \rightarrow \infty} f_n(x) = f(x) \in \mathbb{R}\}$ , so that  $\mu(A) = 1$ . Since  $y \mapsto H_l(x, y)$  is continuous in  $J$  for every  $x \in A$  due to the convexity of  $y \mapsto H_l(x, y)$  and  $\nu$ -a.s. finiteness of  $\psi$ , the subdifferential  $\partial H_l(x, \cdot)(y)$  is nonempty, convex and compact for every  $y \in I = \text{int}(J)$ . This allows us to choose a measurable function  $h_l : A \rightarrow \mathbb{R}$  satisfying  $h_l(x) \in \partial H_l(x, \cdot)(x)$ . Such choice yields (3.11) as follows:

$$f(x) + h_l(x)(y - x) \leq H_l(x, x) + h_l(x)(y - x) \leq H_l(x, y) \leq \psi(y) - c_l(x, y).$$

We may define  $h_l \equiv 0$  on  $\mathbb{R} \setminus A$ , noting that  $f := -\infty$  on  $\mathbb{R} \setminus A$ .

**Step 4.** We will show that for any functions  $\theta_l : \mathbb{R} \rightarrow \mathbb{R}$ ,  $l = 1, \dots, L$  that satisfies (3.11) (whose existence was shown in the previous step), and for any maximizer  $\vec{\gamma}^* = (\gamma_1^*, \dots, \gamma_L^*) \in \mathcal{M}_L(\mu, \nu)$  for the problem (2.7), it holds

$$(3.13) \quad \varphi(x) + \psi(y) + \theta_l(x)(y - x) = c_l(x, y) \quad \gamma_l^* - a.e. \text{ for all } l = 1, \dots, L.$$

For any  $\vec{\gamma} = (\gamma_1, \dots, \gamma_L) \in \mathcal{M}_L(\mu, \nu)$ , Assumption [A] yields  $c_l \in L^1(\gamma_l)$ . We claim

$$\begin{aligned} (3.14) \quad \liminf_{n \rightarrow \infty} \sum_{l=1}^L \int (\varphi_n(x) + \psi_n(y) + \theta_{l,n}(x)(y - x)) d\gamma_l \\ \geq \sum_{l=1}^L \int (\varphi(x) + \psi(y) + \theta_l(x)(y - x)) d\gamma_l \quad \text{for every } l. \end{aligned}$$

To see how the claim implies (3.13), let  $\vec{\gamma}^*$  be any maximizer for (2.7). Then

$$\begin{aligned}
\bar{P}_c &= \lim_{n \rightarrow \infty} \sum_{l=1}^L \int (\varphi_n(x) + \psi_n(y) + \theta_{l,n}(x)(y-x)) d\gamma_l^* \\
&\geq \sum_{l=1}^L \liminf_{n \rightarrow \infty} \int (\varphi_n(x) + \psi_n(y) + \theta_{l,n}(x)(y-x)) d\gamma_l^* \\
&\geq \sum_{l=1}^L \int (\varphi(x) + \psi(y) + \theta_l(x)(y-x)) d\gamma_l^* \\
&\geq \sum_{l=1}^L \int c_l(x, y) d\gamma_l^* = \bar{P}_c,
\end{aligned}$$

hence equality holds throughout. Notice this yields (3.13), hence the proposition.

To prove (3.14), fix any  $\vec{\gamma} = (\gamma_1, \dots, \gamma_L) \in \mathcal{M}_L(\mu, \nu)$ . The nonnegativity (3.1) gives  $\gamma_l^X(\varphi_n) + \gamma_l^Y(\psi_n) \geq 0$ , and (3.2) gives  $\sum_{l=1}^L (\gamma_l^X(\varphi_n) + \gamma_l^Y(\psi_n)) = \mu(\varphi_n) + \nu(\psi_n) \searrow \bar{P}_c$ . This implies the sequence  $\{\gamma_l^X(\varphi_n) + \gamma_l^Y(\psi_n)\}_n$  is bounded for all  $l$ . With this and (3.5), as in Step 2 (but  $\gamma_l^X \preceq_c \gamma_l^Y$  instead of  $\mu \preceq_c \nu$ ), we deduce

$$\sup_n \|\chi_n + \varphi_n\|_{L^1(\gamma_l^X)} < \infty, \quad \sup_n \|\psi_n - \chi_n\|_{L^1(\gamma_l^Y)} < \infty, \quad \text{for all } l.$$

From this, since  $\varphi_n \rightarrow \varphi$ ,  $\psi_n \rightarrow \psi$ ,  $\chi_n \rightarrow \chi$ , by Fatou's lemma, we get

$$\chi + \varphi \in L^1(\gamma_l^X), \quad \psi - \chi \in L^1(\gamma_l^Y),$$

$$\liminf_{n \rightarrow \infty} \int (\chi_n + \varphi_n) d\gamma_l^X \geq \int (\chi + \varphi) d\gamma_l^X, \quad \liminf_{n \rightarrow \infty} \int (\psi_n - \chi_n) d\gamma_l^Y \geq \int (\psi - \chi) d\gamma_l^Y.$$

This allows us to proceed

$$\begin{aligned}
&\liminf_{n \rightarrow \infty} \int (\varphi_n(x) + \psi_n(y) + \theta_{l,n}(x)(y-x)) d\gamma_l \\
&= \liminf_{n \rightarrow \infty} \int (\varphi_n(x) + \chi_n(x) - \chi_n(y) + \psi_n(y) - \chi_n(x) + \chi_n(y) + \theta_{l,n}(x)(y-x)) d\gamma_l \\
&\geq \int (\chi + \varphi) d\gamma_l^X + \int (\psi - \chi) d\gamma_l^Y + \liminf_{n \rightarrow \infty} \int (\chi_n(y) - \chi_n(x) + \theta_{l,n}(x)(y-x)) d\gamma_l.
\end{aligned}$$

To handle the last term, disintegrate  $\gamma_l = (\gamma_l)_x \otimes \gamma_l^X$ , and let  $\xi_n : I \rightarrow \mathbb{R}$  be a sequence of functions satisfying  $\xi_n(x) \in \partial\chi_n(x)$ . This allows us to proceed

$$\begin{aligned} & \int (\chi_n(y) - \chi_n(x) + \theta_{l,n}(x)(y - x)) d\gamma_l \\ &= \iint (\chi_n(y) - \chi_n(x) + \theta_{l,n}(x)(y - x)) (\gamma_l)_x(dy) \gamma_l^X(dx) \\ &= \iint (\chi_n(y) - \chi_n(x) + \xi_n(x)(y - x)) (\gamma_l)_x(dy) \gamma_l^X(dx), \end{aligned}$$

because  $\int \theta_{l,n}(x)(y - x) (\gamma_l)_x(dy) = \int \xi_n(x)(y - x) (\gamma_l)_x(dy) = 0$ . Notice that the last integrand is nonnegative. Thus by repeated Fatou's lemma, we deduce

$$\begin{aligned} & \liminf_{n \rightarrow \infty} \int (\chi_n(y) - \chi_n(x) + \theta_{l,n}(x)(y - x)) d\gamma_l \\ & \geq \int \liminf_{n \rightarrow \infty} \left( \int (\chi_n(y) - \chi_n(x) + \xi_n(x)(y - x)) (\gamma_l)_x(dy) \right) \gamma_l^X(dx) \\ & \geq \int \left( \int (\chi(y) - \chi(x) + \xi(x)(y - x)) (\gamma_l)_x(dy) \right) \gamma_l^X(dx), \end{aligned}$$

for some  $\xi(x) \in \partial\chi(x)$  which is a limit point of the bounded sequence  $\{\xi_n(x)\}_n$ . Finally, in the last line, the inner integral equals

$$\int (\chi(y) - \chi(x) + \theta_l(x)(y - x)) (\gamma_l)_x(dy).$$

This proves the claim, hence the proposition.  $\square$

We are prepared to prove Theorem 1.1.

*Proof of Theorem 1.1.* Fix any optimal pair  $(\pi, \mu_1)$  for the problem (1.2), and let  $\gamma_l = \pi_x \otimes \mu_l$ ,  $l = 1, 2$ , with  $\mu_2 = \mu - \mu_1$  and the kernel  $\{\pi_x\}_x$  inherited from  $\pi$ . We understand  $c_1(x, y) = c_1(x)$  in the proof. Let us first assume that  $\mu \preceq_c \nu$  is irreducible. Then by Proposition 2.3, with  $f = -\varphi$  and  $h_l = -\theta_l$ , we have

$$(3.15) \quad f(x) + h_l(x)(y - x) + c_l(x, y) \leq \psi(y) \quad \text{for each } l = 1, 2 \text{ and } (x, y) \in \mathbb{R}^2,$$

$$(3.16) \quad f(x) + h_l(x)(y - x) + c_l(x, y) = \psi(y) \quad \gamma_l - a.e. (x, y) \text{ for each } l = 1, 2.$$

Now, saying that an American option holder randomizes her exercise between  $c_1, c_2$  is equivalent to saying that the common mass of  $\mu_1, \mu_2$  (written as  $\mu_1 \wedge \mu_2$ ) is nonzero. The common mass of  $\mu_1, \mu_2$  is defined by the largest measure  $\rho = \mu_1 \wedge \mu_2$

satisfying  $\rho \leq \mu_1$  and  $\rho \leq \mu_2$ . Since  $\gamma_1$  and  $\gamma_2$  have the same kernel, (3.16) implies

$$(3.17) \quad f(x) + h_l(x)(y - x) + c_l(x, y) = \psi(y) \quad \pi_x \otimes \rho - a.e. (x, y) \text{ for } l = 1, 2.$$

Observe that  $\psi$  can be taken as  $\psi := \max(\psi_1, \psi_2)$ , where

$$\psi_l(y) := \sup_x f(x) + h_l(x)(y - x) + c_l(x, y),$$

and consequently,  $\psi_1, \psi_2, \psi$  are all convex since  $c_2$  is convex in  $y$  (while  $c_1$  is independent of  $y$ .) Now the idea is to differentiate (3.17) by  $y$  for  $\nu$ -a.e.  $y$ , which is enabled by the fact that  $\psi$  is differentiable  $\nu$ -a.s., since  $\nu$  is assumed to be absolutely continuous with respect to Lebesgue. By the differentiation combined with the first-order optimality condition from (3.15), (3.16) for each  $l = 1, 2$ , we deduce

$$(3.18) \quad h_1(x) = \psi'(y) = h_2(x) + (c_2)_y(x, y) \quad \pi_x \otimes \rho - a.e. (x, y),$$

where  $(c_2)_y$  denotes the partial derivative of  $c_2$  by  $y$ , noting that (3.15), (3.16) implies  $(c_2)_y(x, y)$  exists  $\gamma_2$ -a.e., since  $\psi$  is differentiable  $\nu$ -a.e..

Now since  $c_1 = c_1(x)$ , the left hand side of (3.15) is linear in  $y$  when  $l = 1$ , while  $\psi$  is convex. With this, the first equality in (3.18) implies that for  $\rho$ -a.e.  $x$ ,  $\psi$  is linear in the smallest interval containing  $\text{spt}(\pi_x)$  which contains  $x$ . Hence,

$$(3.19) \quad \psi'(y) = \psi'(x) \quad \pi_x \otimes \rho - a.e. (x, y).$$

The second equality in (3.18) thus becomes

$$(3.20) \quad (c_2)_y(x, y) = \psi'(x) - h_2(x) \quad \pi_x \otimes \rho - a.e. (x, y).$$

Because  $c_2$  is assumed to be strictly convex in  $y$ , the solution  $y$  to (3.20) must be unique, and hence,  $y = x$  since  $\pi_x$  has its barycenter at  $x$ . We conclude

$$(3.21) \quad \pi_x = \delta_x \quad \rho - a.e. x,$$

where  $\delta_x \in \mathcal{P}(\mathbb{R})$  is the Dirac mass at  $x$ . (3.17) then yields

$$(3.22) \quad c_1(x) = c_2(x, x) \quad \rho - a.e. x.$$

Now if  $c_1(x) \neq c_2(x, x)$   $\mu$ -a.s., then (3.22) implies  $\rho \equiv 0$ , yielding  $\mu_1 \perp \mu - \mu_1$  for any optimal pair  $(\pi, \mu_1)$ . This proves the theorem when  $\mu \preceq_c \nu$  is irreducible.

For general  $\mu \preceq_c \nu$ , it is well known that any convex-ordered pair  $(\mu, \nu)$  can be decomposed as at most countably many irreducible pairs, and the decomposition

is uniquely determined by the potential functions  $u_\mu, u_\nu$ . More precisely, we have: [9, Proposition 2.3] Let  $(I_k)_{1 \leq k \leq N}$  be the open components of the open set  $\{u_\mu < u_\nu\}$  in  $\mathbb{R}$ , where  $N \in \mathbb{N} \cup \{+\infty\}$ . Let  $I_0 = \mathbb{R} \setminus \cup_{k \geq 1} I_k$  and  $\mu_k = \mu|_{I_k}$  for  $k \geq 0$ , so that  $\mu = \sum_{k \geq 0} \mu_k$ . There exists a unique decomposition  $\nu = \sum_{k \geq 0} \nu_k$  such that

$$\mu_0 = \nu_0, \text{ and } (\mu_k, \nu_k) \text{ is irreducible for } k \geq 1 \text{ with } \mu_k(I_k) = \mu_k(\mathbb{R}).$$

Moreover, any  $\pi \in \mathcal{M}(\mu, \nu)$  admits a unique decomposition  $\pi = \sum_{k \geq 0} \pi_k$  such that  $\pi_k \in \mathcal{M}(\mu_k, \nu_k)$  for all  $k \geq 0$ .

Here,  $\pi_0$  must be the identity transport, i.e.,  $(\pi_0)_x = \delta_x$ , since it is a martingale transport between the same marginal. Since the theorem has already been proven for the irreducible pairs  $(\mu_k, \nu_k)$ ,  $k \geq 1$ , we only need to prove it for the identity transport  $\pi_0$ . In this case,  $\int c_2(x, y)(\pi_0)_x(dy) = c_2(x, x)$ , yielding that it is optimal to exercise  $c_1$  when  $c_1(x) > c_2(x, x)$ , while it is optimal to exercise  $c_2$  when  $c_1(x) < c_2(x, x)$ . The assumption  $c_1(x) \neq c_2(x, x)$   $\mu$ -a.s. therefore completes the proof.  $\square$

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