

# Approximating Choice Data by Discrete Choice Models\*

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November 9, 2022

## Abstract

We obtain a necessary and sufficient condition under which random-coefficient discrete choice models such as the mixed logit models are rich enough to approximate any nonparametric random utility models across choice sets. The condition turns out to be very simple and tractable. When the condition is *not* satisfied and, hence, there exists a random utility model that cannot be approximated by any random-coefficient discrete choice model, we provide algorithms to measure the approximation errors. After applying our theoretical results and the algorithms to real data, we find that the approximation errors can be large in practice.

*Keywords:* Discrete choice, stochastic choice, mixed logit, random coefficients, finite mixture.

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# 1 Introduction

Random-coefficient discrete choice models are workhorse models in many empirical economics applications. These models have been used to approximate various preferences and capture rich substitution patterns. However, the exact degree of flexibility and the limitations of the random-coefficient models have not yet been fully understood. In this paper, we obtain a necessary and sufficient condition under which parametric random coefficient models can approximate the choice behavior generated by any nonparametric random utility model. The condition turns out to be a simple formula of a few primitives.

We consider the following class of models. Let  $X \subset \mathbf{R}^k$  be the set of all alternatives, where  $k$  is the number of explanatory variables. In an *additive random utility model (ARUM)*, the choice probability of an alternative  $x$  in a choice set  $D \subset X$  is given by  $\rho(D, x) = \mu(\{\varepsilon|u(x) + \varepsilon(x) > u(y) + \varepsilon(y) \forall y \in D \setminus \{x\}\})$ , where  $u$  is a deterministic utility and  $\varepsilon$  is a random utility shock that follows the probability measure  $\mu$ .<sup>1</sup> The class of the ARUMs is general and includes the probit, logit, and nested-logit models as special cases. The *random-coefficient* version of the ARUM is defined as follows. The choice probability is given by

$$\rho(D, x) = \int \mu(\{\varepsilon|u(x) + \eta(x) + \varepsilon(x) > u(y) + \eta(y) + \varepsilon(y) \forall y \in D \setminus \{x\}\}) dm(u), \quad (1)$$

where  $m$  is a probability measure over  $u$  and  $\eta$  is a vector of *fixed effects*. In the standard interpretation,  $m$  captures the heterogeneity of preferences among consumers. The fixed effects  $\eta$  capture the average preference for unobserved characteristics of alternatives.<sup>2</sup> When  $\mu$  is a iid extreme-value type-I distribution, then  $\rho$  reduces to a *mixed logit model*, which is one of the most widely used random-coefficient models (see Train (2009)). Usually, researchers make a parametric assumption on  $u(\cdot)$  in (1), such as  $u(x)$  is a polynomial. In many papers, researchers assume  $u$  is linear (i.e.,  $u(x) = \beta \cdot x$ ). If  $u$  is a polynomial of degree  $d$  *m*-a.s., then the model is called the *degree- $d$  random-coefficient ARUM*.

Given the popularity of the model, it is important to understand its exact extent of flexibility and limitations. For this purpose, we obtain a necessary and sufficient condition under which the degree- $d$  random-coefficient ARUMs are rich enough to

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<sup>1</sup>In this paper, we assume that  $\mu$  has a density function  $f$  and (i) the set  $\{\varepsilon|f(\varepsilon) > 0\}$  is convex and open and (ii) the set includes zero.

<sup>2</sup>Notice that the roles of  $u$  and  $\eta$  are different. The probability measure  $m$  is only on  $u$  but not on  $\eta$ .

approximate any choice probabilities generated by nonparametric random utility models across choice sets. For the approximation target, we choose the random utility models, which are defined as probability measures over rankings on alternatives. This is because the class of the models is one of the most flexible classes in the literature. We study approximation *across choice sets* because many questions of interest (such as substitution patterns) are possible to answer only if we analyze behaviors across choice sets.

When the condition is *not* satisfied, it is important to ask how large the approximation errors can be. To answer this question, we provide algorithms that calculate the approximation errors. Moreover, we apply the algorithms to a real dataset. In the following paragraphs, we will explain the necessary and sufficient condition. Then, we will describe its empirical application to calculate the minimal approximation errors..

In main Theorem 1, we state that the necessary and sufficient condition is the affine-independence of the set  $\{p_d(x)|x \in X\}$ , where  $p_d(x)$  is the vector consisting of monomials of at most degree  $d$  of characteristics  $x$ .<sup>3</sup> One surprising fact about the condition is that it does not depend on the probability measure  $\mu$  over the utility shock  $\varepsilon$ . This implies that if the condition is violated, there exists some choice probabilities generated by a random utility model that cannot be approximated by any degree- $d$  random-coefficient ARUM, no matter which probability measure  $\mu$  of  $\varepsilon$  we use (and no matter which parameters and fixed effects we use).

Although the affine-independence condition is easy to test, the condition is generically equivalent to a further simpler condition:  $|X| \leq \binom{d+k}{k}$ , where  $|X|$  is the number of alternatives,  $k$  is the number of characteristics observed for each alternative, and  $d$  is the degree of polynomial utility functions  $u$ . The number  $\binom{d+k}{k}$  is the number of ways of choosing  $k$  elements out of  $d+k$  elements, which is increasing both in  $d$  and  $k$ . The condition requires that the degree  $d$  of polynomial utility functions and the number  $k$  of coefficients be large enough to satisfy the inequality. The condition is easy to check. For example, when  $d = 1$ , as most papers assume, the condition reduces to  $|X| \leq k + 1$ .

Remember that the affine-independence condition is for the approximation across choice sets. In some cases, researchers may be interested only in fitting a model

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<sup>3</sup>For example, if  $x = (x(1), x(2))$ , then  $p_2(x) = (x(1), x(2), x(1)^2, x(1)x(2), x(2)^2)$  and  $p_1(x) = (x(1), x(2))$ . A set  $Y \equiv \{y_1, \dots, y_n\}$  is *affinely independent* if for any  $y_i \in Y$ , there exists no real number  $\{\mu_j\}_{j \neq i}$  such that  $y_i = \sum_{j \neq i} \mu_j y_j$  and  $\sum_{j \neq i} \mu_j = 1$ . A set  $Y \equiv \{y_1, \dots, y_n\}$  is affinely independent if and only if  $\{y_2 - y_1, \dots, y_n - y_1\}$  is linearly independent. ( $y_1$  can be any  $y_i$ .)

to the observed choice probabilities (i.e., market shares) on the fixed choice set  $X$ . In that case, the necessary and sufficient condition reduces to be the convex-independence of the set  $\{p_d(x)|x \in X\}$  (i.e.,  $p_d(x) \notin \text{co.}\{p_d(y)|y \in X \setminus x\}$  for any  $x \in X$ ), which is weaker than the affine-independence condition.<sup>4</sup> (See Proposition 1.)

In many empirical papers, researchers use *the linear mixed logit models*, that is, the mixed logit models in which  $\mu$  in (1) is a iid extreme-value type-I and utility function  $u$  is linear (i.e.,  $d = 1$  or  $u(x) = \beta \cdot x$ ). In these papers, we find that the convex-independence condition is usually satisfied. On the other hand, the condition that  $|X| \leq k + 1$  is not satisfied in many papers. This means that the linear mixed-logit models are rich enough to approximate observed choice probabilities from a single choice set  $X$ ; however, the models may not be rich enough to approximate the true substitution pattern across subsets of  $X$ , no matter how one chooses the parameters and fixed effects.

In the case in which the affine-independence condition is not satisfied, we propose a method to measure the approximation errors. Our method is based on two algorithms: one algorithm is a variant of the greedy algorithm proposed in Barron et al. (2008). The other algorithm is the EM (Expectation-Maximization) algorithm drawn from Dempster et al. (1977).

We apply our theorem and the two algorithms to a dataset of fishing-site choices from Thomson and Crooke (1991). In the data set,  $k = 2$  and  $|X| = 4$ ; the affine-independence condition with  $d = 1$  is thus violated. We measure the approximation errors by estimating the best possible linear mixed logit model using the greedy algorithm and the EM algorithm. Regardless of the method used, we find that the approximation errors are large and often larger than 10 percentage points on average. Moreover, we demonstrate that in the data set, it is difficult to capture a reasonable substitution pattern by using the linear mixed model.

The rest of the paper is organized as follows. In the next subsection, we discuss the related literature. In section 2, we introduce the models. In section 3, we provide the main results. In section 4, we provide theoretical results for measuring approximation errors. In section 5, we provide an empirical illustration.

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<sup>4</sup>Unlike the affine-independence condition, the convex-independence condition does not have such a simple generic condition. See footnote 15.

## Related Literature

The work most closely related to our paper are Dagsvik (1994) and especially McFadden and Train (2000), who show that any given (nonparametric) continuous random utility model can be approximated by a mixed logit model.<sup>5</sup> Nevertheless, there are important differences to note. In particular, our result holds for a much more general class of random-coefficient ARUMs, including but not confined to the mixed logit models. Second, our result is not only sufficient but also necessary. This is crucial given our purpose of clarifying the exact extent of flexibility and limitations of the random-coefficient ARUMs. Moreover, through our condition, our results provide a tight bound on how many parameters we need for an arbitrarily good approximation. Third, the setup of McFadden and Train (2000) and our setup differ in that McFadden and Train (2000) focus on the case where  $X$  is continuous, while we assume that  $X$  is finite. Hence, neither result implies the other. A recent paper by Lu and Saito (2021a) also studies the extent to which the approximation of continuous random utility is possible by using mixed-logit models.

Another paper related to ours is Norets and Takahashi (2013). They study whether ARUMs can represent any stochastic choice on a fixed choice set. The differences between our paper and their paper come from the fact that they do not study choices across subsets nor do they allow random coefficients. Athey and Imbens (2007) also investigate how a rich specification of the unobserved components (i.e., the fixed effects) is needed to represent any stochastic choice. Their setup is also different from ours in that they focus on logit models.

Our analysis shares some of its spirit with the growing literature that identifies and estimates flexible discrete choice models under minimal assumptions. See, for example, Berry and Haile (2014), Compiani (2022), and Tebaldi et al. (2022). Our paper is also related in motivation to recent studies that apply machine learning to specify flexible utility functions in discrete choice models to improve approximation performance (Bajari et al., 2015; Ruiz et al., 2020; Gillen et al., 2019).

In the decision theory literature, we know of no research that directly relates to our papers. However, logit models and random utility models have been analyzed for a long time ever since Luce (1959) and Block and Marschak (1960).

Recent papers in decision theory have considered generalizations of logit models. These include Gul et al. (2014), Saito (2018) on mixed logit models; Kovach and

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<sup>5</sup>Our result is consistent with their result: heuristically speaking, the result by McFadden and Train (2000) corresponds to the case when  $d = \infty$ , which satisfies our condition.

Tserenjigmid (2020) on nested logit models; Echenique and Saito (2019), Cerreia-Vioglio et al. (2022, 2018), and Horan (2018) on logit models with zero probability choice; and Fudenberg and Strzalecki (2015) on dynamic extensions of logit models. Chambers et al. (2020) and Chambers et al. (2021a) propose variations of the logit models. Apesteguia and Ballester (2018) and Frick et al. (2019) point out the differences in choice behavior between random utility models and logit models.

Gul and Pesendorfer (2006), which axiomatizes the random expected utility theory, has inspired many works that study the random utility model and its generalization. These include Ahn and Sarver (2013), Apesteguia, Ballester and Lu (2017), Lin (2019), and Chambers, and Masatlioglu and Turansick (2021b), as well as Lu (2016, 2021) on extensions to choice under uncertainty, and Lu and Saito (2018), Duraj (2018), Frick, Iijima and Strzalecki (2019), and Lu and Saito (2021b) on dynamic extensions.

## 2 Model

### 2.1 Setup

**Set of alternatives:** The set of all alternatives is denoted by  $X$ .  $X$  is assumed to be finite. An alternative  $x$  is described by a real vector of explanatory variables of the alternative. For example, if an alternative is a consumption good, the alternative is described by its price and its various other characteristics. Hence, we let  $X$  be a finite subset of  $\mathbf{R}^k$ , where  $k$  is the number of the explanatory variables. For each  $x \in X$  and  $l \in \{1, \dots, k\}$ , we write  $x(l)$  to denote the  $l$ -th element of  $x$ .

This notation may not be common in the empirical literature, where researchers often use another set  $J$  of indices of alternatives. In the standard notation in the literature, each  $j \in J$  is an index for each alternative and its characteristic vector is written as  $x_j \in X$ . To simplify the notation, in this paper, we identify  $j$  and  $x_j$  and use the vector  $x \in X$  itself to denote the alternative.

**Choice sets:** Let  $\mathcal{D} \subset 2^X \setminus \{\emptyset\}$  be the set of choice sets. Notice that  $\mathcal{D}$  can be a proper subset of  $2^X \setminus \emptyset$ . Unless otherwise noted, throughout the paper we assume that  $\{x, y\} \in \mathcal{D}$  and  $\{x, y, z\} \in \mathcal{D}$  for any  $x, y, z \in X$ . In some parts of the paper, however, we drop this assumption and assume that  $\mathcal{D} = \{X\}$  when we consider the case in which an econometrician's purpose is fitting a model to the observed choice probabilities from the single choice set.

The set  $\mathcal{D}$  may contain both observed choice sets as well as hypothetical choice sets the econometrician is interested in. For example, even when the econometrician observes consumers' choices only over  $\{\text{train, bus, car}\}$ , he may also be interested in choices over  $\{\text{train, bus}\}$ ,  $\{\text{train, car}\}$ , and  $\{\text{bus, car}\}$  to learn the consumers' substitution pattern.

**Stochastic choice function:** A function  $\rho : \mathcal{D} \times X \rightarrow [0, 1]$  is called a *stochastic choice function* if  $\sum_{x \in D} \rho(D, x) = 1$  and  $\rho(D, x) = 0$  for any  $x \notin D$ . The set of stochastic choice functions is denoted by  $\mathcal{P}$ . For each  $(D, x) \in \mathcal{D} \times X$ , the number  $\rho(D, x)$  is the probability that an alternative  $x$  is chosen from a choice set  $D$ . In a context of empirical industrial organization, for example,  $\rho(D, x)$  can be interpreted as a market share of product  $x$  in a market in which the set of available products is  $D$ . We interpret the stochastic choice function  $\rho$  as aggregate choice probabilities across individuals.

**Rankings:** Let  $\Pi$  be the set of bijections between  $X$  and  $\{1, \dots, |X|\}$ , where  $|X|$  is the number of elements of  $X$ . For any element  $\pi \in \Pi$ , if  $\pi(x) = i$ , then we interpret  $x$  to be the  $|X| + 1 - i$ -th best element of  $X$  with respect to  $\pi$ . If  $\pi(x) > \pi(y)$ , then  $x$  is better than  $y$  with respect to  $\pi$ . An element  $\pi$  of  $\Pi$  is called a *strict preference ranking* (or simply, a *ranking*) over  $X$ . For all  $(D, x) \in \mathcal{D} \times X$  such that  $x \in D$ , if  $\pi(x) > \pi(y)$  for all  $y \in D \setminus \{x\}$ , then we often write  $\pi(x) \geq \pi(D)$ . There are  $|X|!$  elements in  $\Pi$ .

## 2.2 Models

We denote the set of probability measures over  $\Pi$  by  $\Delta(\Pi)$ . Since  $\Pi$  is finite,  $\Delta(\Pi) = \{(\nu_1, \dots, \nu_{|\Pi|}) \in \mathbf{R}_+^{|\Pi|} \mid \sum_{i=1}^{|\Pi|} \nu_i = 1\}$ , where  $\mathbf{R}_+$  is the set of nonnegative real numbers.

We now introduce the definition of random utility models:

**Definition 1.** A stochastic choice function  $\rho$  is called a *random utility model* if there exists a probability measure  $\nu \in \Delta(\Pi)$  such that for all  $(D, x) \in \mathcal{D} \times X$ , if  $x \in D$ , then

$$\rho(D, x) = \nu(\pi \in \Pi \mid \pi(x) \geq \pi(D)).$$

The set of random utility models is denoted by  $\mathcal{P}_r$ .<sup>6</sup>

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<sup>6</sup>While the function above is often called a random ranking function, a random utility model is often defined differently—by using the existence of a probability measure  $\mu$  over utilities such that for all  $(D, x) \in \mathcal{D} \times X$ , if  $x \in D$ , then  $\rho(D, x) = \mu(u \in \mathbf{R}^X \mid u(x) \geq u(D))$ . Block and Marschak (1960)'s

Notice that when  $\mathcal{D} = \{X\}$ , the restriction of random utility is vacuous: any stochastic choice function is a random utility model (i.e.,  $\mathcal{P}_r = \mathcal{P}$ ).<sup>7</sup>

To introduce the additive random utility models (ARUMs), we introduce some notations and definitions. Given a positive integer  $d$  and  $x \in X$ , the vector  $p_d(x)$  consists of *monomials* of at most degree  $d$  (i.e., higher order terms such as  $x(l)^n$  where  $n \leq d$ , and interaction terms such as  $\prod_{l=1}^k x(l)^{n_l}$ , where  $\sum_{l=1}^k n_l \leq d$ ).<sup>8</sup> Notice that  $p_d(x) = x$  when  $d = 1$ .

**Definition 2.** A probability measure on the Borel  $\sigma$ -algebra of  $\mathbb{R}^{|X|}$  is said to be *standard* if (i) it is absolute continuous with respect to the Lebesgue measure and (ii) the set  $\{\varepsilon | f(\varepsilon) > 0\}$  is convex and open; and (iii)  $0 \in \{\varepsilon | f(\varepsilon) > 0\}$ , where  $f$  is the density function of  $\mu$ .<sup>9</sup>

**Definition 3.** Let  $d$  be a positive integer and  $\eta \in \mathbf{R}^{|X|}$  be a real vector. A stochastic choice function  $\rho$  is called a *degree- $d$  additive-random utility model (ARUM) with fixed effects  $\eta$*  if there exists a standard probability measure  $\mu$  and real vector  $\beta$  such that, for all  $(D, x) \in \mathcal{D} \times X$ , if  $x \in D$ , then

$$\rho(D, x) = \mu(\{\varepsilon | \beta \cdot p_d(x) + \eta(x) + \varepsilon(x) > \beta \cdot p_d(y) + \eta(y) + \varepsilon(y) \text{ for all } y \in D \setminus \{x\}\}),$$

where  $\beta \cdot p_d(x)$  is a polynomial of  $x$  of at most degree  $d$ . When  $d = 1$ , then we say the function is *linear* instead of *degree-1*. The set of degree- $d$  ARUMs with fixed effects  $\eta$  and probability measure  $\mu$  is denoted by  $\mathcal{P}_a(d, \eta | \mu)$ . Let  $\mathcal{M}$  be the set of all standard probability measures.

We give two comments on ARUMs. First, we consider the models with fixed effects given their popularity in empirical applications. Fixed effects are used frequently to capture the average preference for unobserved characteristics of alternatives (Berry et al., 1995).

Second, many probability measures are standard and the class of ARUMs is rich. For a logit model,  $\mu$  is a iid extreme-value type-I distribution; for a probit

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Theorem 3.1 proves that the two definitions are equivalent.

<sup>7</sup>To see this, observe that  $\mathcal{P}_r \subset \mathcal{P}$  by definition. We show the converse. For any  $x \in X$ , let  $\pi_x \in \Pi$  such that  $\pi_x(x) > \pi_x(y)$  for all  $y \in D$ . Then  $\rho^{\pi_x}(y) = 1_x(y)$  for any  $y \in X$ , where  $1_x(y) = 1$  if  $y = x$  and  $1_x(y) = 0$  if  $y \neq x$ . For any  $\rho \in \mathcal{P}$ , define  $\rho' = \sum_{x \in X} \rho(x) \rho^{\pi_x}$ . Then,  $\rho' \in \mathcal{P}_r$  and  $\rho'(x) = \rho(x)$  for any  $x \in X$ , as desired. Hence,  $\mathcal{P} \subset \mathcal{P}_r$ .

<sup>8</sup>We do not include monomials of degree 0 (i.e., constants). For example, if  $k = 2$  and  $d = 2$ , then  $p_d(x) = (x(1), x(2), x(1)^2, x(1)x(2), x(2)^2)$  where  $x = (x(1), x(2))$ . The order of elements in  $p_d(x)$  does not matter.

<sup>9</sup>The density exists because of (i).



model,  $\mu$  is the multivariate standard normal distribution; for a nested logit model,  $\mu$  is a generalized extreme value distribution (Train, 2009). On the other hand, the definition excludes some extreme correlations. The condition that the set  $\{\varepsilon|f(\varepsilon) > 0\}$  is open and includes zero implies that any shock  $\varepsilon(x)$  can be greater or less than another shock  $\varepsilon(y)$ .<sup>10</sup> The openness of the set  $\{\varepsilon|f(\varepsilon) > 0\}$  in  $\mathbf{R}^{|X|}$  also excludes extreme correlation such as  $\varepsilon(x) = \varepsilon(y)$  almost surely for some  $x, y \in X$ .

The next definition is a random-coefficient version of the ARUMs.

**Definition 4.** Let  $d$  be a positive integer and  $\eta \in \mathbf{R}^{|X|}$  be a real vector. A stochastic choice function  $\rho$  is called a *degree- $d$  random-coefficient ARUM with fixed effects  $\eta$*  if there exist a standard probability measure  $\mu$  and a Borel probability measure  $m$  such that for all  $(D, x) \in \mathcal{D} \times X$ , if  $x \in D$ , then

$$\rho(D, x) = \int \mu(\{\varepsilon|\beta \cdot p_d(x) + \eta(x) + \varepsilon(x) > \beta \cdot p_d(y) + \eta(y) + \varepsilon(y) \forall y \in D \setminus \{x\}\}) dm(\beta).$$

When  $m$  has a finite support, then  $\rho$  is called a *finite mixture* of degree- $d$  ARUMs. The set of degree- $d$  random-coefficient ARUMs with probability measure  $\mu$  and fixed effects  $\eta$  is denoted by  $\mathcal{P}_{ra}(d, \eta|\mu)$ . When the context makes clear which standard probability measure  $\mu$  we are considering, we omit the word “with distribution  $\mu$ .”

A widely used special case of the above models is the *mixed logit models*.

**Definition 5.** Let  $d$  be a positive integer and  $\eta \in \mathbf{R}^{|X|}$  be a real vector. A stochastic choice function  $\rho$  is called a *degree- $d$  mixed logit model with fixed effects  $\eta$*  if there exists a Borel probability measure  $m$  such that for all  $(D, x) \in \mathcal{D} \times X$ , if  $x \in D$ , then

$$\rho(D, x) = \int \frac{\exp(\beta \cdot p_d(x) + \eta(x))}{\sum_{y \in D} \exp(\beta \cdot p_d(y) + \eta(y))} dm(\beta). \quad (2)$$

The set of degree- $d$  mixed logit models with fixed effects  $\eta$  is denoted by  $\mathcal{P}_{ml}(d, \eta)$ . When  $m$  is degenerate (that is, when  $m = \delta_\beta$  for some  $\beta$ ) in (2), then  $\rho$  is called a *logit model*. The set of degree- $d$  logit models with fixed effects  $\eta$  is denoted by  $\mathcal{P}_l(d, \eta)$ . The set of all logit models (of any degree and with any fixed effects)  $\bigcup_{(d, \eta) \in \mathbf{Z}_+ \times \mathbf{R}^{|X|}} \mathcal{P}_l(d, \eta)$  is denoted by  $\mathcal{P}_l$ .

As mentioned, if  $\mu$  is a iid extreme-value type-I distribution, then  $\mathcal{P}_a(d, \eta|\mu) = \mathcal{P}_l(d, \eta)$ , and  $\mathcal{P}_{ra}(d, \eta|\mu) = \mathcal{P}_{ml}(d, \eta)$ , for any  $(d, \eta)$ . Note that in most empirical

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<sup>10</sup>Formally, for any  $x, y \in X$ ,  $\mu(\{\varepsilon|\varepsilon(x) > \varepsilon(y)\}) > 0$ . We used this property in the proof of Lemma 2.

applications of the mixed logit models, the mixing distribution is usually a parametric distribution like a multivariate normal distribution. In our case, the mixing distributions of the random coefficients do not come from a particular parametric family.

Finally, we review essential mathematical concepts. A *polytope* is a convex hull of finitely many points. The closure of a set  $C$  is denoted by  $\text{cl}.C$  with respect to the standard finite dimensional Euclidean topology. The *affine hull* of a set  $C$  is the smallest affine set that contains  $C$ , and it is denoted by  $\text{aff}.C$ . The convex hull of a set  $C$  is denoted by  $\text{co}.C$ . The *relative interior* of a convex set  $C$  is the interior of  $C$  in the relative topology with respect to  $\text{aff}.C$ . The relative interior of  $C$  is denoted by  $\text{rint}.C$ .

### 3 Main Result

To state the main result of the paper, we review a basic concept in geometry: A set  $Y \subset \mathbb{R}^n$  is *affinely independent* if no element in  $Y$  can be written as an affine combination of the other elements.<sup>11</sup> It is easy to see that a set  $Y \equiv \{y_1, \dots, y_n\}$  is affinely independent if and only if  $\{y_2 - y_1, \dots, y_n - y_1\}$  is linearly independent.<sup>12</sup>

**Theorem 1.** *Let  $d$  be a positive integer.*

(i) *Let  $\mu$  be any standard probability measure. If the set  $\{p_d(x)|x \in X\}$  is affinely independent, then any random utility model can be approximated by a degree- $d$  random-coefficient ARUM. Moreover, the approximation can be done with a finite mixture of degree- $d$  ARUMs without fixed effects (i.e.,  $\eta = 0$ ). That is,*

$$\forall \mu \in \mathcal{M} \forall \rho \in \mathcal{P}_r \exists \rho_n \in \text{co}.\mathcal{P}_a(d, 0|\mu) \forall x \in D \in \mathcal{D} [\rho_n(D, x) \rightarrow \rho(D, x)].$$

(ii) *If the set  $\{p_d(x)|x \in X\}$  is not affinely independent, then there exists a random utility model that cannot be approximated by any degree- $d$  random-coefficient ARUM with any sequence of fixed effects and with any standard probability measure  $\mu$ . That is,*

$$\exists \rho \in \mathcal{P}_r \forall \mu \in \mathcal{M}, \rho \notin \text{cl.} \bigcup_{\eta \in \mathbf{R}^{|X|}} \mathcal{P}_{ra}(d, \eta|\mu).$$

<sup>11</sup>Formally, for any  $y \in Y$ ,  $y \notin \text{aff}.(Y \setminus \{y\})$ . That is, for any  $y \in Y$ , there exists no real number  $\{\mu_x\}_{x \in X}$  such that  $y = \sum_{x \in Y \setminus \{y\}} \mu_x x$  and  $\sum_{x \in Y \setminus \{y\}} \mu_x = 1$ .

<sup>12</sup>Instead of subtracting  $y_1$  from  $y_{i \neq 1}$ , we can subtract any  $y_i$  from  $y_{j \neq i}$ .

Notice that the condition (i.e., the affine-independence of  $\{p_d(x)|x \in X\}$ ) does *not* depend on the probability measure  $\mu$ .<sup>footnote</sup>As we will explain in the sketch of proof, this independence from the choice of a probability measure is originated from the fact that the set of random utility model is polytope. This implies that if the affine-independence condition holds, then the approximation is possible with *any* probability measure  $\mu \in \mathcal{M}$ . Thus, the econometrician may use any standard probability measure which is convenient for her.

On the other hand, if the affine-independence condition fails, then there exists a random utility model that cannot be approximated by any degree- $d$  random-coefficient ARUM, no matter which fixed effects  $\eta$  and no matter which probability measure  $\mu$  we use. For example, the approximation is impossible using any degree- $d$  mixed logit model nor any degree- $d$  random-coefficient probit-model. In Proposition 2 in Section 4, we will give examples of the random utility models that cannot be approximated.

Although testing for affine-independence is easy, the condition can be simplified further to a generically equivalent condition. To see this, note that, for any  $x \in X$  and any positive integer  $d$ ,  $p_d(x)$  is a  $\binom{d+k}{k} - 1$  dimensional real vector. Remember this basic fact: for any set  $Y \subset \mathbb{R}^n$ , (i) if  $|Y| > n + 1$ , then  $Y$  is not affinely independent; (ii) if  $|Y| \leq n + 1$ , then  $Y$  is generically affinely independent.<sup>13</sup> Given these observations, Theorem 1 implies the following corollary:

**Corollary 1.** *Let  $d$  be a positive integer.*

- (i) *If  $|X| \leq \binom{d+k}{k}$ , then the statements in Theorem 1 (i) hold generically.*
- (ii) *If  $|X| > \binom{d+k}{k}$ , then the statements in Theorem 1 (ii) hold.*

We now mention three remarks on the results in order. First, most empirical applications assume that  $d = 1$ . Hence, the generic necessary and sufficient condition becomes  $|X| \leq k + 1$ . We use this condition for our empirical application in Section 5. Second, note that if  $X$  is affinely independent, then it remains to be affinely independent even with small perturbations. This reflects the fact that what is important in the generic condition is the number of alternatives (i.e.,  $|X|$ ), not  $X$  itself. Third, even though the generic condition holds, the original condition

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<sup>13</sup>This is a standard concept of genericity in the literature of discrete geometry. Even if a set  $Y \subset \mathbb{R}^n$  is not affinely independent, then, as long as  $|Y| \leq n + 1$ , for any  $\varepsilon > 0$ , there exists an affinely independent set  $Y'$ , obtained from  $Y$  by moving each point by a distance of at most  $\varepsilon$  (see Section 3 of Matousek (2013)).

of the affine independence may not hold when explanatory variables include zeroes and ones. In that case, one should check the affine-independence of  $\{p_d(x)|x \in X\}$ , rather than the generic condition.

In the following, we provide a supplemental result for the case in which  $\mathcal{D} = \{X\}$ . Such a case corresponds to a situation in which the econometrician is interested only in fitting a model with the observed choice probabilities (i.e., market shares) on a single set  $X$  (but not on its subsets).

**Proposition 1.** *Assume that  $\mathcal{D} = \{X\}$ . Let  $d$  be a positive integer.*

(i) *Let  $\mu$  be any standard probability measure. If the set  $\{p_d(x)|x \in X\}$  is convex-independent (i.e., if  $p_d(x) \notin \text{co.}\{p_d(y)|y \in X \setminus x\}$  for any  $x \in X$ ), then any random utility model can be approximated by a degree- $d$  random-coefficient ARUM; moreover, the approximation can be done with a finite mixture of degree- $d$  ARUMs without fixed effects (i.e.,  $\eta = 0$ ). That is,*

$$\forall \mu \in \mathcal{M} \quad \forall \rho \in \mathcal{P}_r \quad \exists \rho_n \in \text{co.}\mathcal{P}_a(d, 0|\mu) \quad \forall x \in X \quad \rho_n(X, x) \rightarrow \rho(X, x).$$

(ii) (a) *If the set  $\{p_d(x)|x \in X\}$  is not convex-independent, then there exists a random utility model that cannot be approximated by any degree- $d$  random-coefficient ARUMs with any probability measure  $\mu$  and without fixed effects (i.e.,  $\eta = 0$ ). That is,  $\exists \rho \in \mathcal{P}_r \quad \forall \mu \in \mathcal{M} \quad \rho \notin \text{cl.}\mathcal{P}_{ra}(d, 0|\mu)$ .*

(b) *However, if fixed effects are used, any random utility model can be approximated by an ARUM with any standard probability measure  $\mu$ .*

Note that the convex-independence condition is weaker than the affine-independence condition. This makes sense because the convex-independence condition guarantees the approximation only on the single choice set (i.e.,  $\{X\}$ ), while the affine-independence condition guarantees the approximation across all subsets  $D \in \mathcal{D}$  of  $X$  (including  $X$  itself).

The implications of Theorem 1 and Proposition 1 are similar. One important difference arises when the conditions (i.e., the affine-independence condition in Theorem 1 and the convex-independence condition in Proposition 1) are violated. In both cases, there exists a random utility model that cannot be approximated *without* using fixed effects. However, as stated in Proposition 1 (ii)(b), if fixed effects are used, any random utility model can be approximated. (This result directly follows from Norets and Takahashi (2013).) This is in contrast to Theorem 1 (ii), which

claims that there exists a random utility model that cannot be approximated even using any fixed effects.<sup>14</sup>

Unlike the affine-independence, the convex-independence does not restrict the number of elements in a convex-independent set.<sup>15</sup> Thus, there exists no counterpart of Corollary 1.

### 3.1 Applied Implications

To conclude this section, we mention the implications of the theorem and the proposition to the empirical literature. Most empirical papers use the linear mixed logit model (i.e.,  $d = 1$  and  $\mu$  is a iid extreme-value type-I distribution). In the papers, the convex-independence condition is usually satisfied. That is, it is often the case that any alternative  $x$  lies outside the convex hull  $\text{co.}(X \setminus \{x\})$  of the other alternatives. In fact, we will see this is the case in a dataset in section 5.

On the other hand, the condition that  $|X| \leq k + 1$  is often violated. (Remember that  $|X|$  is the number of alternatives and  $k$  is the number of characteristics.) There are many choice situations in which  $|X|$  is very large such as choices of groceries, hospitals, cars, schools, or restaurants etc. In such a dataset, the condition is likely to be violated. *This means that the linear model is rich enough to describe the choice data from a single choice set; however, the model may not be rich enough to approximate the true substitution pattern, no matter how one chooses parameters and fixed effects.*<sup>16</sup> Thus, researchers might want to increase the degree of polynomial or the number of characteristic variables to satisfy the affine-independence condition.<sup>17</sup> At least, they might want to be aware of the limitation of the linear models. In Section 5, we quantify these limitation of the linear models using a real dataset.

In the next subsection 3.2, we provide a sketch of proof. The sketch gives geometric insights about our results. Moreover, some concepts (Definitions 6 and 7) will be used in section 5. Readers who may not be interested in the proofs may skip the following subsection by skimming Definitions 6 and 7.

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<sup>14</sup>This difference originates from the fact that we require approximation on all  $D \in \mathcal{D}$  in Theorem 1, while in Proposition 1, we require approximation only on  $X$ .

<sup>15</sup> For example, in three-dimensional space  $(x, y, z)$ , consider a circumference of radius one whose origin is  $(0, 0, 1)$  on a hyperplane of  $z = 1$ . The number of points on the circumference is a continuum. However, the set of points on the circumference is convex-independent.

<sup>16</sup>By substitution patterns we mean how choice probabilities change in different choice sets.

<sup>17</sup>We address possible over-fitting problems in the Online Appendix.

### 3.2 Proof Sketch: Lemmas

We prove Theorem 1 and Proposition 1 by using the five lemmas below. We first consider models without fixed effects (i.e.,  $\eta = 0$ ). First we define a notation: for each ranking  $\pi \in \Pi$ , define

$$\rho^\pi(D, x) = \begin{cases} 1 & \text{if } \pi(x) > \pi(y) \text{ for all } y \in D \setminus x; \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

The function  $\rho^\pi$  gives probability one to the best alternative  $x$  in a choice set  $D$  according to the strict preference ranking  $\pi$ . The following fact is elementary but fundamental:

**Observation:** *The set  $\mathcal{P}_r$  of random utility models is a polytope, that is,  $\mathcal{P}_r = \text{co.}\{\rho^\pi \mid \pi \in \Pi\}$ .*

The observation holds because for any random utility model  $\rho \in \mathcal{P}_r$ , we have  $\rho = \sum_{\pi \in \Pi} \nu(\pi) \rho^\pi$ , where  $\nu$  is the probability measure rationalizing the random utility model. The hexagons in Figure 2 further below illustrate the polytope.<sup>18</sup>

**Lemma 1.**

1. *Let  $\mathcal{Q}$  be a subset of  $\mathcal{P}_r$ . Then  $\mathcal{P}_r = \text{cl.co.}\mathcal{Q}$  if and only if, for any  $\pi \in \Pi$ , there exists a sequence  $\{\rho_n\}_{n=1}^\infty$  of  $\mathcal{Q}$  such that  $\rho_n \rightarrow \rho^\pi$ .*
2. *Let  $\mathcal{Q}$  be a subset of  $\text{rint.}\mathcal{P}_r$ . Then  $\text{rint.}\mathcal{P}_r = \text{co.}\mathcal{Q}$  if and only if, for any  $\pi \in \Pi$ , there exists a sequence  $\{\rho_n\}_{n=1}^\infty$  of  $\mathcal{Q}$  such that  $\rho_n \rightarrow \rho^\pi$ .*
3.  *$\mathcal{P}_l \subset \text{rint.}\mathcal{P}_r$ .*

Parts (1) and (2) of Lemma 1 give conditions under which random utility models can be approximated by a convex combination of elements of  $\mathcal{Q}$ . We will use the lemma with  $\mathcal{Q} = \mathcal{P}_a(d, 0 \mid \mu)$  for some  $\mu \in \mathcal{M}$  (the set of degree- $d$  ARUMs with probability measure  $\mu$  and without fixed effects).

The next lemma makes it easier for us to check the conditions of Lemma 1. First we introduce a definition.

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<sup>18</sup>Although the geometric intuition is useful, it is important to notice that the figure oversimplifies the reality since the number (i.e.,  $|X|!$ ) of vertices and the dimension of a random utility model can be very large. To see why the dimension of a random utility model can be very large, notice that it assigns a number for each pair of  $(D, x) \in \mathcal{D} \times X$ . We calculate the dimension later in Proposition 4.

**Definition 6.** For any positive integer  $d$ , a ranking  $\pi \in \Pi$  is *degree- $d$ -representable* in choice sets  $\mathcal{D}$  if there exists a real vector  $\beta$  such that, for all  $D \in \mathcal{D}$  and  $x \in D$ ,

$$\pi(x) > \pi(y) \text{ for all } y \in D \setminus \{x\} \Leftrightarrow \beta \cdot p_d(x) > \beta \cdot p_d(y) \text{ for all } y \in D \setminus \{x\}. \quad (4)$$

**Lemma 2.** *Let  $d$  be a positive integer. For any ranking  $\pi \in \Pi$ , the following statements hold:*

1. *If  $\pi$  is degree- $d$ -representable, then for any  $\mu \in \mathcal{M}$ , there exists a sequence  $\{\rho_n\}_{n=1}^\infty$  of  $\mathcal{P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$ .*
2. *If  $\pi$  is not degree- $d$ -representable, then there exists no probability measure  $\mu \in \mathcal{M}$  such that there exists a sequence  $\{\rho_n\}_{n=1}^\infty$  of  $\text{co.}\mathcal{P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$ .*

Notice that for any ranking, checking the degree- $d$ -representability is easy.<sup>19</sup> Thus, Lemma 1 and Lemma 2 provide a testable condition under which the degree- $d$  random-coefficient ARUMs without fixed effects are flexible enough to approximate any random utility model.

Although checking the representability of a particular ranking is easy, checking the representability of all rankings may be computationally prohibitive. This is because the number of rankings equals  $|X|!$  and can be large. To overcome this problem, we obtain a simple necessary and sufficient condition for any ranking  $\pi \in \Pi$  to be degree- $d$  representable:

**Lemma 3.** *Let  $d$  be a positive integer.*

1. *Any ranking is degree- $d$ -representable in  $\mathcal{D}$  if and only if the set  $\{p_d(x)|x \in X\}$  is affinely independent.*
2. *Any ranking is degree- $d$ -representable in  $\{X\}$  if and only if the set  $\{p_d(x)|x \in X\}$  is convex-independent.*

To understand Lemma 3 (1) geometrically, see Figure 1. In the figure, we assume that  $k = 2$ ; we consider linear models (i.e.,  $p_d(x) = x$ ) in Figure 1 (a) and (b), and quadratic models (i.e.,  $d = 2$ ) in Figure 1 (c), respectively. In Figure 1 (a), the set  $X = \{x, y, z\}$  is affinely independent. Thus, by Lemma 3 (1) (the “if” part), any ranking is degree-1-representable. For example, the ranking  $\pi(x) > \pi(y) >$

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<sup>19</sup>By definition, checking the representability condition is equivalent to finding a solution to a system of finite linear inequalities defined by (4).

$\pi(z)$  is degree-1-representable by  $\beta \in \mathbf{R}^2$ , which defines the parallel hyperplanes (indifference curves) in Figure 1 (a).

On the other hand, in Figure 1 (b), the set  $X = \{x, y, z, w\}$  is not affinely independent. The ranking  $\pi(x) > \pi(w) > \pi(z) > \pi(y)$  is not degree-1-representable. As the figure shows, no matter how one chooses  $\beta \in \mathbf{R}^2$  and draws parallel hyperplanes as indifference curves, it does not hold that  $\beta \cdot x > \beta \cdot w > \beta \cdot z > \beta \cdot y$ . The existence of such a unrepresentable ranking is implied by the “only if” part of Lemma 3 (1).<sup>20</sup>

If we use ellipses as indifference curves, however, we can represent the ranking  $\pi(x) > \pi(w) > \pi(z) > \pi(y)$  as in Figure 1 (c). The existence of such curves is again implied by the “if” part of Lemma 3 (1) since ellipses can be defined with at most degree-2 polynomials and the generic condition with  $d = 2$  is satisfied (i.e.,  $|X| = 4 \leq 6 = \binom{4}{2} = \binom{d+k}{k}$ ) in this example.<sup>21</sup>

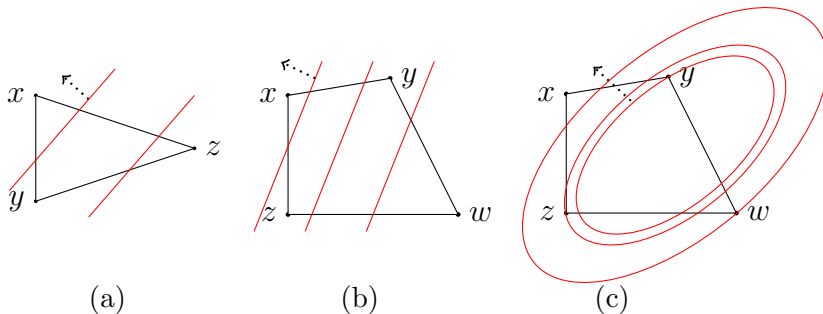


Figure 1: Illustration of the affine-independence condition.

Lemma 3 (2) is more straightforward. To see this, consider  $d = 1$  for simplicity and notice that when  $\mathcal{D} = \{X\}$ , any  $\pi \in \Pi$  is degree-1 representable in  $\{X\}$  if and only if, for any  $x \in X$ , there exists  $\beta$  such that  $\beta \cdot x > \beta \cdot y$  for all  $y \in X \setminus x$ , which means that  $X$  is convex-independent. By using Lemmas 1, 2, and 3, we obtain parts (i) of Theorem 1 and Proposition 1.

Remember that so far we have assumed no fixed effects (i.e.,  $\eta = 0$ ). In the following, we analyze the extent to which random utility models can be approximated by using fixed effects. In particular, we show that if the affine independence condition fails then there exists a random utility model that cannot be approximated even with using fixed effects.

<sup>20</sup>The slope of the “indifference” line must be steeper than the slope of the line segment  $(z, y)$  (because  $\pi(z) > \pi(y)$ ) and less steep than the slope of the line segment  $(z, x)$  (because  $\pi(x) > \pi(w)$ ), which together imply that  $\beta \cdot z > \beta \cdot w$ .

<sup>21</sup>In fact, we verified that the affine-independence condition is satisfied with  $d = 2$ .



First, we will see the usefulness of the fixed effects. It is easy to observe that when  $\mathcal{D} = \{X\}$ , any stochastic choice can be approximated by using fixed effects.<sup>22</sup> Even for general  $\mathcal{D}$ , the following holds:

**Observation:** *For any ranking  $\pi$ ,  $\rho^\pi$  can be approximated by an ARUM with fixed effects.*<sup>23</sup>

However, this may not be enough to approximate any random utility model. As an illustration, consider two fixed effects,  $\eta_1$  and  $\eta_2$ , and see Figure 2 below. Remember that in the heuristic figure, the hexagon represents  $\mathcal{P}_r = \text{co.}\{\rho^\pi | \pi \in \Pi\}$ . Given a degree  $d$ , the two convex sets in the hexagon correspond to  $\mathcal{P}_{ra}(d, \eta_1 | \mu)$  and  $\mathcal{P}_{ra}(d, \eta_2 | \mu)$  shaded orange and blue, respectively.<sup>24</sup> Notice that all vertices in the figure can be approximated by elements of  $\mathcal{P}_{ra}(d, \eta_1 | \mu)$  or  $\mathcal{P}_{ra}(d, \eta_2 | \mu)$ . However, some areas of the hexagon are not covered by either  $\mathcal{P}_{ra}(d, \eta_1 | \mu)$  or  $\mathcal{P}_{ra}(d, \eta_2 | \mu)$ .

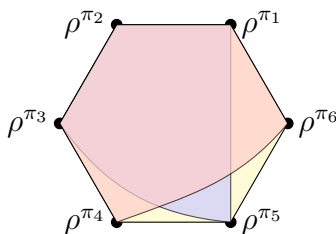


Figure 2: Illustration of  $\mathcal{P}_{ra}(d, \eta_1 | \mu)$  and  $\mathcal{P}_{ra}(d, \eta_2 | \mu)$

In reality, the problem is more complicated since we need to consider the union of all possible values of fixed effects, and thus the union of the continuum of convex sets  $\mathcal{P}_{ra}(d, \eta | \mu)$  across all values of  $\eta \in \mathbf{R}^{|X|}$ .<sup>25</sup> Moreover, we need to consider all possible standard probability measure  $\mu \in \mathcal{M}$ . Nevertheless, Lemma 4 provides a clear answer and state that if there exists a degree- $d$  unrepresentable ranking, then

<sup>22</sup>This is intuitive since we can choose  $|X|$  parameters (i.e.,  $\{\eta(x)\}_{x \in X}$ ) to fit  $|X|$  data points (i.e.,  $\{\rho(X, x)\}_{x \in X}$ ).

<sup>23</sup>To see this fix  $\pi$  and choose  $\eta \in \mathbf{R}^X$  such that  $\eta(x) > \eta(y)$  if and only if  $\pi(x) > \pi(y)$ . Then, it can be shown that an ARUM  $\rho_n$  defined by  $\rho_n(D, x) = \mu(\{\varepsilon | n\eta(x) + \varepsilon(x) \geq n\eta(y) + \varepsilon(y) \text{ for all } y \in D \setminus \{x\}\})$  converges to  $\rho^\pi(D, x)$  as  $n \rightarrow \infty$ .

<sup>24</sup>To see this notice that  $\mathcal{P}_{ra}(d, \eta | \mu)$  is a random utility model and convex.

<sup>25</sup>More formally, the difficulty arises because the set of all degree- $d$  ARUMs with probability measure  $\mu$  and with any fixed effects (i.e.,  $\bigcup_{\eta \in \mathbf{R}^X} \text{co.}\mathcal{P}_a(d, \eta | \mu)$ ) may not be convex, although given  $\eta$ , each set  $\text{co.}\mathcal{P}_a(d, \eta | \mu)$  is convex. This is because mixtures can be taken only over  $\beta$  but not over  $\eta$ . Thus approximating vertices is not enough for approximation over the polytope of random utility models.

there exists a random utility model that cannot be approximated, no matter which fixed effects and probability distribution we use.

First we introduce a new notation.

**Definition 7.** For any ranking  $\pi \in \Pi$ , define  $\pi^- \in \Pi$  such that  $\pi(x) > \pi(y)$  if and only if  $\pi^-(y) > \pi^-(x)$  for any  $x, y \in X$ . The ranking  $\pi^-$  is called the *reverse* ranking of  $\pi$ .

**Lemma 4.** Let  $\mu$  be a standard probability measure. For any  $\alpha \in (0, 1)$  and any ranking  $\pi$  that is not degree- $d$ -representable, there exists a neighborhood  $U$  of  $\alpha\rho^\pi + (1 - \alpha)\rho^{\pi^-}$  such that any random utility model that belongs to  $U$  cannot be approximated by any degree- $d$  random-coefficient ARUM with any fixed effects. That is,  $\forall \rho \in \mathcal{P}_r \cap U$ ,  $\rho \notin \text{cl.} \bigcup_{\eta} \mathcal{P}_{ra}(d, \eta | \mu)$ .

To prove the lemma, we need to prove the following two statements: (a) any strict convex combination between  $\rho^\pi$  and  $\rho^{\pi^-}$  cannot be approximated by a degenerate ARUM with fixed effects; and (b) moreover it cannot be approximated by a nondegenerate random-coefficient ARUM even with any fixed effects. We prove statement (a) in the appendix. To show statement (b), we introduce the following concept:

**Definition 8.** The two rankings  $\pi$  and  $\pi'$  are *adjacent* if there exists  $t \in \mathbf{R}^{\mathcal{D} \times X}$  and  $a \in \mathbf{R}$  such that (i)  $\rho^\pi \cdot t = a = \rho^{\pi'} \cdot t$ , and (ii) for any  $\hat{\pi}$ , if  $\pi \neq \hat{\pi} \neq \pi'$ , then  $\rho^{\hat{\pi}} \cdot t > a$ .<sup>26</sup>

For example, in Figure 2,  $\rho^{\pi^i}$  and  $\rho^{\pi^{i+1}}$  are adjacent for each  $i \leq 5$ . Since  $\pi$  and  $\pi^-$  are reversed with each other,  $\rho^\pi$  and  $\rho^{\pi^-}$  seem very different. It turns out, however, that they are adjacent:<sup>27</sup>

**Lemma 5.** For any ranking  $\pi \in \Pi$ ,  $\rho^\pi$  and  $\rho^{\pi^-}$  are adjacent.

The characterization of adjacency of vertices for the case  $\mathcal{D} = 2^X \setminus \emptyset$  appears in Doignon and Saito (2022). Lemma 5 holds even for the case in which  $\mathcal{D} \neq 2^X \setminus \emptyset$  as long as  $\mathcal{D}$  contains all binary and trinary sets.<sup>28</sup> The lemma allows us to complete the proof of Lemma 4 as follows. If  $\pi$  is not degree- $d$  representable, then

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<sup>26</sup> $t \in \mathbf{R}^{\mathcal{D} \times X}$  is a vector that gives a real number for each pair of  $(D, x) \in \mathcal{D} \times X$ . For any  $\rho \in \mathcal{P}$ ,  $\rho \cdot t = \sum_{(D, x) \in \mathcal{D} \times X} \rho(D, x)t(D, x)$ .

<sup>27</sup>Our discussions with Jean-Paul Doignon and Haruki Kono were very helpful for obtaining this result.

<sup>28</sup>We are grateful to Haruki Kono for pointing out this fact.

$\pi^-$  is also not degree- $d$  representable. Although fixed effects are powerful enough to approximate each vertex  $\rho^\pi$ , we will prove that it is not powerful enough to approximate both  $\rho^\pi$  and  $\rho^{\pi^-}$  by using the same fixed effects, intuitively because  $\rho^\pi$  and  $\rho^{\pi^-}$  are reversed. Thus, no strict convex combination of  $\rho^\pi$  and  $\rho^{\pi^-}$  can be approximated by the degree- $d$  random-coefficient ARUMs with probability measure  $\mu$ , no matter which fixed effects we use. Notice that this conclusion does *not* follow if  $\rho^\pi$  and  $\rho^{\pi^-}$  are not adjacent since a strict convex combination of  $\rho^\pi$  and  $\rho^{\pi^-}$  may be represented in a different way. This proves statement (b) and thus, Lemma 4. Lemmas 1, 2, 3, and 4 prove statement (ii) of Theorem 1, as the proof in the appendix formalizes.

## 4 Measuring Approximation Errors

In this section, we study the following question: When the condition in the theorem is not satisfied, how large are the approximation errors?

We first define the distance function as follows: For any  $\rho, \hat{\rho} \in \mathcal{P}$ , define  $d(\rho, \hat{\rho}) = \|\rho - \hat{\rho}\|/|\mathcal{D}|$ , where  $\|\cdot\|$  is the Euclidean norm.<sup>29</sup> In our analysis,  $\hat{\rho}$  is a given stochastic choice function;  $\rho$  is a random-coefficient ARUM by which we approximate  $\hat{\rho}$ . The distance  $d(\rho, \hat{\rho})$  captures the average distance between  $\rho$  and  $\hat{\rho}$ . For example,  $d(\rho, \hat{\rho}) = 0.1$  means that on average across choice sets, the estimated stochastic choice function  $\rho$  is distant from the given stochastic choice function  $\hat{\rho}$  by 10 percentage points.

Given an approximation target  $\hat{\rho} \in \mathcal{P}_r$  and a standard probability measure  $\mu$ , when researchers use degree- $d$  random-coefficient ARUMs with fixed effects  $\eta$ , the approximation error is defined as:

$$\inf_{\rho \in \mathcal{P}_{ra}(d, \eta | \mu)} d(\rho, \hat{\rho}). \quad (5)$$

We call (5) the *approximation error to  $\hat{\rho}$*  by degree- $d$  random-coefficient ARUMs with fixed effects  $\eta$ . To calculate the maximal approximation error, we need to specify a random utility model  $\hat{\rho}$  that cannot be approximated. Proposition 2 gives an idea about how to choose  $\hat{\rho}$ .

**Proposition 2.** *Let  $\mu$  be any standard probability measure. Let  $d$  be a positive*

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<sup>29</sup>Remember  $\|\hat{\rho} - \rho\| = \sqrt{\sum_{(x,D) \in X \times \mathcal{D}} (\hat{\rho}(D,x) - \rho(D,x))^2}$ .

integer. If  $\{p_d(x)|x \in X\}$  is not affinely independent, then for each ranking  $\pi$  that is not degree- $d$ -representable, the following statements hold:<sup>30</sup>

- (i) There exists a neighborhood  $U$  of  $\rho^\pi$  such that any random utility model that belongs to  $U$  cannot be approximated by any degree- $d$  random-coefficient ARUM without fixed effects. That is,  $\forall \rho \in \mathcal{P}_r \cap U, \rho \notin \text{cl.}\mathcal{P}_{ra}(d, 0|\mu)$ .
- (ii) For each  $\alpha \in (0, 1)$ , there exists a neighborhood  $U$  of  $\alpha\rho^\pi + (1 - \alpha)\rho^{\pi^-}$  such that any random utility model that belongs to  $U$  cannot be approximated by any degree- $d$  random-coefficient ARUMs with any sequence of fixed effects. That is,  $\forall \rho \in \mathcal{P}_r \cap U, \rho \notin \text{cl.}\bigcup_\eta \mathcal{P}_{ra}(d, \eta|\mu)$ .

Note that the proposition holds with any standard probability measure. As for the second statement (ii), remember that by using fixed effects, we can approximate any  $\rho^\pi$ . However, approximating a mixture between  $\rho^\pi$  and  $\rho^{\pi^-}$  is impossible even using fixed effects when  $\pi$  is not representable.

Given  $\hat{\rho}$ , we use two algorithms to solve (5) and compute the approximation errors. The first is the standard EM (Expectation-Maximization) algorithm. The second algorithm is a greedy algorithm. We provide an explanation of these algorithms in section A in the appendix.

## 5 Application to Data

In this section, we quantify approximation errors with and without fixed effects, by using data on fishing-site choices from Thomson and Crooke (1991).<sup>31</sup> The data have been used by Herriges and Kling (1999) and Cameron and Trivedi (2005) (p.464). In the data set, 1182 individuals choose among 4 alternative fishing modes, namely,  $X = \{x_{\text{beach}}, x_{\text{boat}}, x_{\text{charter}}, x_{\text{pier}}\}$ , which denote fishing from the beach, a private boat, a charter boat or a pier, respectively. Each alternative  $x \equiv (x(1), x(2))$  is described by two characteristics (i.e.,  $k = 2$ ). The first characteristic  $x(1)$  is the fishing mode's price, while the other characteristic  $x(2)$  is the *catch rate*, defined as a per-hour-fished basis for each major species by fishing mode.<sup>32</sup>

Throughout this section, we will focus on the mixed logit models (i.e., let  $\mu$  be a iid extreme-value type-I distribution) since they are the most widely used models.

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<sup>30</sup>If  $\{p_d(x)|x \in X\}$  is not affinely independent, then such a ranking exists.

<sup>31</sup>The dataset is taken directly from the R package 'mlogit' by Croissant (2020).

<sup>32</sup>In the original study, the values of  $x(1)$  and  $x(2)$  depend on each individual. For our analysis, we aggregate them by taking the average over individuals. The Online Appendix provides more details.

We also assume that  $\mathcal{D} = 2^X \setminus \emptyset$ . Thus  $\dim \mathcal{P}_r = \sum_{D \in \mathcal{D}} (|D| - 1) = 3 + 2 \times 4 + 1 \times 6 = 17$  by Proposition 4 in section A.1. It is therefore without loss of generality to assume that the number  $M$  of mixtures is less than or equal to 18.

## 5.1 Application of Theorem 1

By Theorem 1,  $X$  is affinely independent if and only if the class of linear (degree-1) mixed logit models with fixed effects is flexible enough to approximate any random utility model. In the data set, we have  $|X| = 4$  alternatives and  $k = 2$  characteristics. Thus, the condition in Corollary 1 is violated (i.e.,  $|X| = 4 \not\leq k + 1 = 3$ ) and  $X$  is not affinely independent. This observation motivates us to compute approximation errors of the linear mixed logit models without fixed effects (in subsection 5.2) and the errors with fixed effects (in subsection 5.3).

On the other hand, with  $d = 2$ , the generic condition for representability in Corollary 1 is satisfied, since  $4 = |X| \leq \binom{2+2}{2} = 6$ . In fact, we verified that  $\{p_d(x) | x \in X\}$  is affinely independent when  $d = 2$ . Thus, by Theorem 1, the degree-2 mixed logit models should be flexible enough to approximate any random utility model. This theoretical implication is also empirically verified below.

## 5.2 Approximation Errors without Fixed Effects

In this section, we obtain approximation errors without fixed effects. By Proposition 2, there exists a ranking  $\pi$  that is not degree-1-representable and corresponding deterministic choice functions  $\rho^\pi$  that are not approximated by any linear mixed logit model without fixed effects. Since there are four alternatives, there are twenty four rankings. Among them, twelve rankings are not degree-1 representable, and thus cannot be approximated by linear mixed logit models, as shown in Table 1.

The table shows the approximation errors of the degree-1 or degree-2 mixed logit models obtained by the greedy algorithm and the EM algorithm. In both algorithms, the approximation errors for degree-1-unrepresentable rankings  $\pi$  are almost always larger than 0.1, which means that even the best possible linear mixed logit model deviates from the corresponding choice probabilities  $\rho^\pi$  by 10 percent or more on average. Some errors are much larger. For example, the approximation errors of the two rankings  $\pi(1) > \pi(2) > \pi(3) > \pi(4)$  and  $\pi(1) > \pi(2) > \pi(4) > \pi(3)$  by the linear mixed logit models are more than 0.2. Notice that these two rankings are the only rankings in which the alternative 1 (i.e., beach) is the best and the alternative

Table 1: Approximation errors to preference rankings  $\rho^\pi$

Ranking $\pi$ (1)	$d = 1$		$d = 2$	
	Greedy (2)	EM (3)	Greedy (4)	EM (5)
Degree-1-Unrepresentable Rankings				
$\pi(1) > \pi(2) > \pi(3) > \pi(4)$	0.218	0.227	0.000	0.000
$\pi(1) > \pi(2) > \pi(4) > \pi(3)$	0.202	0.211	0.000	0.000
$\pi(1) > \pi(3) > \pi(2) > \pi(4)$	0.128	0.115	0.000	0.000
$\pi(1) > \pi(4) > \pi(2) > \pi(3)$	0.126	0.165	0.000	0.000
$\pi(2) > \pi(1) > \pi(3) > \pi(4)$	0.138	0.147	0.000	0.000
$\pi(2) > \pi(1) > \pi(4) > \pi(3)$	0.118	0.123	0.000	0.000
$\pi(3) > \pi(2) > \pi(4) > \pi(1)$	0.091	0.096	0.000	0.000
$\pi(3) > \pi(4) > \pi(1) > \pi(2)$	0.121	0.128	0.000	0.000
$\pi(3) > \pi(4) > \pi(2) > \pi(1)$	0.149	0.160	0.000	0.000
$\pi(4) > \pi(2) > \pi(3) > \pi(1)$	0.113	0.115	0.000	0.000
$\pi(4) > \pi(3) > \pi(1) > \pi(2)$	0.157	0.155	0.000	0.000
$\pi(4) > \pi(3) > \pi(2) > \pi(1)$	0.182	0.185	0.000	0.000
Degree-1-Representable Rankings	0.000	0.000	0.000	0.000

Note: The numbers in the table show the approximation errors to each  $\rho^\pi$ , where each preference ranking  $\pi$  is defined in Column (1). Alternative numbers 1, 2, 3, 4 denote beach, boat, charter, pier, respectively. For each ranking, columns (2) and (3) show the approximation errors of the linear mixed logit models computed by the greedy algorithm and the EM algorithm, respectively. Columns (4) and (5) show the approximation errors of the degree-2 (quadratic) mixed logit models calculated by each algorithm. All numbers are rounded to three decimal places. For the greedy algorithm we set the number of iterations to 1000. For the EM algorithm we set the number of random initial points to 10.

2 (i.e., private boat) is the second-best. This means that as long as we use the linear mixed logit models, no matter how we choose parameters, it is difficult to capture the *substitution patterns* from the alternative 1 to the alternative 2 (i.e, the change of consumer’s choices from the alternative 1 to the alternative 2) when the alternative 1 is removed from the set of alternatives.

#### Add new results

On the other hand, the approximation error for a degree-1-representable ranking  $\pi$  is almost always zero, as the theorem predicts, as shown in the bottom row of the table. Also, the approximation errors by degree-2 mixed logit models are also almost zero, as the theorem again predicts (column (4) and (5) in the table).

Table 2: Approximation errors to random utility models  $\frac{1}{2}\rho^\pi + \frac{1}{2}\rho^{\pi^-}$

Ranking $\pi$ (1)	$d = 1$		$d = 2$	
	Greedy (2)	EM (3)	Greedy (4)	EM (5)
Degree-1-Unrepresentable Rankings				
$\pi(1) > \pi(2) > \pi(3) > \pi(4)$	0.069	0.077	0.000	0.000
$\pi(1) > \pi(2) > \pi(4) > \pi(3)$	0.069	0.079	0.000	0.000
$\pi(1) > \pi(3) > \pi(2) > \pi(4)$	0.049	0.077	0.000	0.000
$\pi(1) > \pi(4) > \pi(2) > \pi(3)$	0.049	0.052	0.000	0.000
$\pi(2) > \pi(1) > \pi(3) > \pi(4)$	0.058	0.075	0.000	0.000
$\pi(2) > \pi(1) > \pi(4) > \pi(3)$	0.058	0.060	0.000	0.000
Degree-1-Representable Rankings	0.000	0.000	0.000	0.000

*Notes:* The numbers in the table show the approximation errors to  $\frac{1}{2}\rho^\pi + \frac{1}{2}\rho^{\pi^-}$ , where  $\pi$  is defined in Column (1). All numbers are rounded to three decimal places. For the greedy algorithm we set the number of iterations to 1000. For the EM algorithm we set the number of random initial points to 10.

### 5.3 Approximation Errors with Fixed Effects

In this section, we obtain the approximation errors with fixed effects. By using fixed effects, we can approximate  $\rho^\pi$  for any ranking  $\pi$ . By Proposition 2, however, for each degree-1-unrepresentable ranking  $\pi$  and each  $\alpha \in (0, 1)$ , any random utility model in a neighborhood of  $\alpha\rho^\pi + (1 - \alpha)\rho^{\pi^-}$  cannot be approximated by the linear mixed logit models with fixed effects. In Table 2, we show the approximation error to  $\frac{1}{2}\rho^\pi + \frac{1}{2}\rho^{\pi^-}$  for each degree-1-unrepresentable ranking.

In both algorithms, the approximation errors to  $\frac{1}{2}\rho^\pi + \frac{1}{2}\rho^{\pi^-}$  are always larger than around 5 percent if  $\pi$  is not degree-1-representable. This means that even the best possible linear mixed logit model deviates from  $\frac{1}{2}\rho^\pi + \frac{1}{2}\rho^{\pi^-}$  by 5 percentage points or more on average.

On the other hand, the approximation errors to  $\frac{1}{2}\rho^\pi + \frac{1}{2}\rho^{\pi^-}$  are almost zero, if  $\pi$  is representable, as the theorem predicts. Also, the approximation errors by degree-2 mixed logit models are also almost zero, as the theorem again predicts.

Overall, the widely-used linear mixed logit models fail to approximate random utility models in this data set. The approximation errors are also substantial. This result demonstrates how the affine-independence condition in Theorem 1 provides a simple way to check whether a random-coefficient model can provide a good approximation of random utility models. A more practical implication is that researchers

might want to increase the degree of polynomial or the number of characteristic variables to satisfy the affine-independence condition. (Given this implication of increasing the degree of polynomial or the number of characteristic variables, a natural concern is the overfitting problem. We address this concern in the Online Appendix.) The researchers at least might want to be aware of this limitation of the linear models.

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## A Appendix: Algorithms

### A.1 EM Algorithm

We use the EM algorithm to estimate random-coefficient ARUM that maximizes the likelihood taking  $\hat{\rho}$  as the observed choice probabilities. The Online Appendix shows that the resulting model is indeed a solution to (5) when the affine-independence condition is satisfied. One difficulty to use the EM algorithm in our problem is that it is not clear how many mixtures to include. To overcome this difficulty, in this subsection, we provide a theoretical result that simplifies the set of random-coefficient ARUMs and provides guidance about how many mixtures we need to use.

The first result (Proposition 3) shows that any (continuous) mixture model can be represented as a finite mixture as long as the set of alternatives is finite. The second result (Proposition 4) characterizes the affine hull of the random utility models, which allows us to calculate the dimension of the set of random utility models. This, in turn, gives us an upper bound on the number of mixtures through Caratheodory’s theorem.

**Proposition 3.** *Let  $\mathcal{Q}$  be a subset of the set of stochastic choice functions. Then  $\{\int \rho dm(\rho) | m \in \Delta(\mathcal{Q})\} = co.\mathcal{Q}$ , where  $\Delta(\mathcal{Q})$  denotes the set of probability measures over  $\mathcal{Q}$ .*

The proof is in the Online Appendix. This proposition implies that focusing on finite mixtures is without loss of generality as long as  $X$  is finite. In particular, it

implies that the set  $\mathcal{P}_{ra}(d, \eta|\mu) = \text{co.}\mathcal{P}_a(d, \eta|\mu)$  for any  $d, \eta, \mu$ .<sup>33</sup> Although Proposition 3 reduces  $\mathcal{P}_{ra}(d, \eta|\mu)$  to  $\text{co.}\mathcal{P}_a(d, \eta|\mu)$ , the set  $\text{co.}\mathcal{P}_a(d, \eta|\mu)$  is still big since it contains any (finite) number of mixtures of degree- $d$  ARUMs. By Caratheodory’s theorem, however, there turn out to be at most  $\dim \mathcal{P}_r + 1$  elements.

**Corollary 2.** *Let  $\mu \in M$ . For any positive integer  $d$  and any  $\eta \in \mathbf{R}^{|X|}$ ,  $\mathcal{P}_{ra}(d, \eta|\mu) = \text{co.}\mathcal{P}_a(d, \eta|\mu) = \{ \sum_{m=1}^M \lambda_m \rho_m \mid \rho_m \in \mathcal{P}_a(d, \eta|\mu), \lambda_m \geq 0 \forall m = 1, \dots, M, \sum_{m=1}^M \lambda_m = 1 \}$ , where  $M = \dim \mathcal{P}_r + 1$ .*

To obtain the number  $\dim \mathcal{P}_r$ , we characterize the affine hull of the set  $\mathcal{P}_r$  of random utility models.

**Proposition 4.** *The affine hull of  $\mathcal{P}_r$  is  $\mathcal{P}_{\pm} \equiv \{ q \in \mathbf{R}^{\mathcal{D} \times X} \mid (i) \sum_{x \in D} q(D, x) = 1 \forall D \in \mathcal{D}; (ii) q(D, x) = 0 \forall x \notin D \in \mathcal{D} \}$ . Hence  $\dim \mathcal{P}_r \equiv \dim \mathcal{P}_{\pm} = \sum_{D \in \mathcal{D}} (|D| - 1)$ .*

The proof is in Section B.8. Corollary 2 and Proposition 4 imply that in order to obtain the closest random-coefficient model to the observed choice probabilities, it is sufficient to consider finite mixture models with at most  $1 + \sum_{D \in \mathcal{D}} (|D| - 1)$  mixtures. For example, in section 5, we analyze a choice data with  $|X| = 4$ . These results imply that it is enough to consider the finite mixture models with at most 18 mixtures if one considers the whole choice sets (i.e.,  $\mathcal{D} = 2^X \setminus \emptyset$ ).

## A.2 Greedy Algorithm

Even with the modification proposed in the previous subsection, the EM algorithm may converge only to a local minimum (Dempster et al., 1977).<sup>34</sup> This concern motivates us to propose a second algorithm, the greedy algorithm, which is inspired by Barron et al. (2008). This algorithm has the useful feature that, given the setup of our problem, it will always return a global minimum (up to small approximation errors which can be made arbitrarily small by increasing the number of steps).

The algorithm takes a stochastic choice function  $\hat{\rho}$  and a fixed effects vector  $\eta$  as input and returns a solution to (5). The algorithm is iterative: each step seeks to optimize based on the results of previous steps:

- **Step 1:** Given  $\hat{\rho}$ , choose  $\rho^1$  such that  $\rho^1 = \arg \inf_{\rho \in \text{cl.}\mathcal{P}_a(d, \eta|\mu)} \|\hat{\rho} - \rho\|^2$ .

<sup>33</sup>This result may not hold when  $X$  is continuous. See Lu and Saito (2021).

<sup>34</sup>To alleviate this problem, in the empirical illustration, we run the EM algorithm multiple times, each time with a random initial value.

- **Step  $n$ ,  $n \geq 2$ :**
  - Consider a set of grids  $\alpha_n = \{\frac{2}{k+1}\}_{k=1}^n$ .
  - Find  $(\alpha_n^*, \rho_n^*) = \arg \inf_{(\alpha, \rho) \in \alpha_n \times \text{cl. } \mathcal{P}_a(d, \eta | \mu)} \|\hat{\rho} - (1 - \alpha)\rho^{n-1} - \alpha\rho\|^2$ .
  - Define  $\rho^n = (1 - \alpha_n^*)\rho^{n-1} + \alpha_n^*\rho_n^*$  and let  $\rho^{\text{out}} = \rho^n$ .
- Stop if a terminating criterion is reached.
- Return  $\rho^{\text{out}}$  at the final step.

The next proposition shows that the algorithm will converge quickly.

**Proposition 5.** *Let  $\hat{\rho} \in \mathcal{P}$  be any stochastic function and  $d$  be a positive integer,  $\eta \in \mathbf{R}^{|X|}$ , and  $\mu \in \mathcal{M}$ . Define  $d^* = \inf_{\rho \in \mathcal{P}_{ra}(d, \eta | \mu)} d(\rho, \hat{\rho})$ . Let  $n$  denote the number of steps and  $\rho^n$  denote the output after the completion of the  $n$ -th step of the algorithm. Then there exists a  $T$  such that*

$$d(\rho^n, \hat{\rho}) - d^* \leq \sqrt{\frac{T}{n+1}}, \quad (6)$$

where  $T$  can be chosen to depend only on  $|\mathcal{D}|$ .

The proof is in Section B.9. For our implementation, the terminating criterion is when the number of steps taken reaches 1000. With 1000 steps, (6) implies the margin of error is within 0.026.<sup>35</sup> When we approximate  $\hat{\rho}$  without fixed effects, we let  $\eta = 0$ . When we approximate  $\hat{\rho}$  with fixed effects, we couple the algorithm with a grid of fixed effects to search for the minimum.

## B Appendix: Proofs

### B.1 Proof of Theorem 1

Lemma 1,2, and 3 –(1) imply statements (i) of Theorem 1 and Proposition 1. Statements (ii) of Theorem 1 and Proposition 1 follow from Lemma 1,2, 3–(1), and 4.

### B.2 Proof of Proposition 1

Lemma 1,2, and 3 –(2) imply statement (i) and parts of statement (ii) of Proposition 1. The last statement of statement (ii) can be proved as follows. Consider any

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<sup>35</sup>This is calculated by computing the constant  $T$  in Proposition 5. In our case, the  $T$  is equal to  $88/121$ , so the margin of error is  $\sqrt{88/(121 \times 1001)} \approx 0.026$ . See footnote 45 for the full calculation.

stochastic choice function  $\rho$ . Then there exists a sequence of stochastic choice functions  $\{\rho_n\}$  such that  $\rho_n \rightarrow \rho$  and  $\rho_n(X, x) > 0$  for any  $x \in X$ . Fix  $\mu \in \mathcal{M}$ . Note that our assumption of the convexity of the support implies the connectedness. By Corollary 1 of Norets and Takahashi (2013),  $\rho_n$  can be represented as the ARUMs.

## B.3 Proof of Lemma 1

### B.3.1 Statement (1)

If direction is obvious, we prove only if direction. By assumption,  $\mathcal{P}_r = \text{cl.co.}\mathcal{Q} = \text{co.cl.}\mathcal{Q}$ , where the last equality holds because  $\mathcal{Q}$  is bounded and by Theorem 17.2 of Rockafellar (2015). Since  $\mathcal{P}_r = \text{co.cl.}\mathcal{Q}$ , for any  $\pi \in \Pi$ , there exist positive numbers  $\{\lambda_i\}_{i=1}^m$  such that  $\sum_{i=1}^m \lambda_i = 1$  and a convergent sequence  $\{\rho_n^i\}_{n=1}^\infty$  of  $\mathcal{Q}$  for each  $i \in \{1, \dots, m\}$  such that  $\sum_{i=1}^m \lambda_i \rho_n^i \rightarrow \sum_{i=1}^m \lambda_i \rho^i = \rho^\pi$  as  $n \rightarrow \infty$ , where  $\rho_n^i \rightarrow \rho^i$ . Since  $\rho^\pi$  is a vertex of  $\mathcal{P}_r$  and thus an exposed point<sup>36</sup>,  $\rho^i = \rho^\pi$  for all  $i$ .

### B.3.2 Statement (2)

Let  $\mathcal{Q}$  be any subset of  $\text{rint.}\mathcal{P}_r$ . We will show that  $\text{rint.}\mathcal{P}_r = \text{co.}\mathcal{Q}$  if and only if for any  $\pi \in \Pi$  there exists a sequence  $\{\rho_n\}_{n=1}^\infty$  of  $\mathcal{Q}$  such that  $\rho_n \rightarrow \rho^\pi$  as  $n \rightarrow \infty$ .

*Step 1:* We will show the if part of the statement. Suppose by way of contradiction that there exists  $\rho \in \text{rint.}\mathcal{P}_r \setminus \text{co.}\mathcal{Q}$ . Because  $\text{co.}\mathcal{Q} \neq \emptyset$ , we obtain  $\text{rint.co.}\mathcal{Q} \neq \emptyset$ . Since  $\rho \notin \text{co.}\mathcal{Q}$ , by the proper separating hyperplane theorem (Theorem 11.3 of Rockafellar (2015)), there exist  $t \in \mathbf{R}^{\mathcal{D} \times X} \setminus \{0\}$  and  $a \in \mathbf{R}$  such that

$$\rho \cdot t \geq a \geq \rho' \cdot t \text{ for any } \rho' \in \text{co.}\mathcal{Q} \text{ and } a > \rho'' \cdot t \text{ for some } \rho'' \in \text{co.}\mathcal{Q}. \quad (7)$$

We obtain a contradiction by two substeps.

*Step 1.1:* We show there exists  $\hat{\rho} \in \mathcal{P}_r$  such that  $\hat{\rho} \cdot t > \rho \cdot t$ . To prove the step, remember that there exists  $\rho'' \in \text{co.}\mathcal{Q}$  such that  $\rho'' \cdot t < \rho \cdot t$ . Moreover, since  $\mathcal{Q} \subset \mathcal{P}_r$  and  $\mathcal{P}_r$  is convex, it follows that  $\rho'' \in \text{co.}\mathcal{Q} \subset \mathcal{P}_r$ . Since  $\rho \in \text{rint.}\mathcal{P}_r$ , there exists  $\lambda > 1$  such that  $\lambda\rho + (1 - \lambda)\rho'' \in \mathcal{P}_r$ . Moreover,  $(\lambda\rho + (1 - \lambda)\rho'') \cdot t = \lambda\rho \cdot t + (1 - \lambda)\rho'' \cdot t = \rho \cdot t + (\lambda - 1)(\rho \cdot t - \rho'' \cdot t) > \rho \cdot t$ , where the last inequality holds because  $\lambda > 1$  and  $\rho'' \cdot t < \rho \cdot t$ . So  $\lambda\rho + (1 - \lambda)\rho'' \in \mathcal{P}_r$ .

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<sup>36</sup>A point of a convex set is an exposed point if there is a supporting hyperplane which contains no other points of the set (Rockafellar (2015), Page 162)

*Step 1.2:* There exists  $\rho' \in \text{co.}\mathcal{Q}$  such that  $\rho' \cdot t > \rho \cdot t$ , which contradicts with (7). To prove the step, let  $\hat{\rho}$  be as in Substep 1.1. Since  $\hat{\rho} \in \mathcal{P}_r$ , there exist nonnegative numbers  $\{\hat{\lambda}_\pi\}_{\pi \in \Pi}$  such that  $\hat{\rho} = \sum_{\pi \in \Pi} \hat{\lambda}_\pi \rho^\pi$  and  $\sum_{\pi \in \Pi} \hat{\lambda}_\pi = 1$ .

By the supposition of the lemma, for any  $\pi \in \Pi$ , there exists a sequence  $\{\rho'_n\}_{n=1}^\infty$  of  $\mathcal{Q}$  such that  $\rho'_n \rightarrow \rho^\pi$  as  $n \rightarrow \infty$ . Therefore, for any  $\pi \in \Pi$  and any positive number  $\varepsilon$ , there exists  $\rho'_\pi \in \{\rho'_n\}_{n=1}^\infty$  such that  $\|\rho'_\pi - \rho^\pi\| < \varepsilon$ . Define  $\rho' = \sum_{\pi \in \Pi} \hat{\lambda}_\pi \rho'_\pi$ . Then  $\rho' \in \text{co.}\mathcal{Q}$  and  $\|\rho' - \hat{\rho}\| = \|\sum_{\pi \in \Pi} \hat{\lambda}_\pi (\rho'_\pi - \rho^\pi)\| \leq \sum_{\pi \in \Pi} \hat{\lambda}_\pi \|\rho'_\pi - \rho^\pi\| \leq \sum_{\pi \in \Pi} \hat{\lambda}_\pi \varepsilon = \varepsilon$ . Therefore,  $|\rho' \cdot t - \hat{\rho} \cdot t| \leq \|t\| \|\rho' - \hat{\rho}\| \leq \|t\| \varepsilon$ . Since  $t \cdot \hat{\rho} > t \cdot \rho$ , then by choosing  $\varepsilon$  small enough, we obtain  $\rho' \cdot t > \rho \cdot t$ .

*Step 2:* We will show the only if part of the statement. Since  $\text{rint.}\mathcal{P}_r = \text{co.}\mathcal{Q}$ , we have  $\mathcal{P}_r = \text{cl.}\mathcal{P}_r = \text{cl.rint.}\mathcal{P}_r = \text{cl.co.}\mathcal{Q} = \text{co.cl.}\mathcal{Q}$ , where the first equality holds because  $\mathcal{P}_r$  is closed, the second equality holds by Theorem 6.3 of Rockafellar (2015), and the last equality holds because  $\mathcal{Q}$  is bounded and by Theorem 17.2 of Rockafellar (2015). The rest of the proof goes through exactly the same way as in the only if part of Statement (1).

### B.3.3 Statement (3)

Fix  $\rho \in \mathcal{P}_l$ . Let  $\beta$  and  $\eta$  be the coefficients and fixed effects associated with  $\rho$ . Since  $\rho \in \mathcal{P}_r$ , there exists  $\nu \in \Delta(\Pi)$  such that  $\nu$  rationalizes  $\rho$ . Moreover, in the construction of  $\nu$  in Block and Marschak (1960), they obtain that for any  $\pi \in \Pi$ ,  $\nu(\pi) = \prod_{n=1}^{|X|} \frac{\exp(\beta \cdot p_d(x_n) + \eta(x_n))}{\sum_{l=1}^{|X|} \exp(\beta \cdot p_d(x_l) + \eta(x_l))} > 0$ , where  $X = \{x_1, x_2, \dots, x_{|X|}\}$  and  $\pi(x_1) > \pi(x_2) > \dots > \pi(x_{|X|})$ . Since  $\nu(\pi) > 0$  for all  $\pi \in \Pi$ , it follows from Theorem 6.9 in Rockafellar (2015) that  $\rho \in \text{rint.co.}\{\rho^\pi | \pi \in \Pi\} = \text{rint.}\mathcal{P}_r$ , where the last equality holds because  $\mathcal{P}_r = \text{co.}\{\rho^\pi | \pi \in \Pi\}$ .

## B.4 Proof of Lemma 2

*Step 1:* For any  $\pi \in \Pi$  and any  $\mu \in \mathcal{M}$ , if a ranking  $\pi$  is degree- $d$ -representable, then there exists a sequence  $\{\rho_n\}$  of  $\mathcal{P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$ .

*Proof.* Assume that a ranking  $\pi$  is degree- $d$ -representable. Without loss of generality, assume that  $X = \{x_1, \dots, x_{|X|}\}$  and  $\pi(x_1) > \pi(x_2) > \dots > \pi(x_{|X|})$ . Then there exists  $\beta$  such that for any  $D \in \mathcal{D}$ ,  $\pi(x) > \pi(y)$  for all  $y \in D \setminus \{x\}$  if and only if  $\beta \cdot p_d(x) > \beta \cdot p_d(y)$  for all  $y \in D \setminus \{x\}$ . For any positive integer  $n$  and any

$(D, x) \in \mathcal{D} \times X$  such that  $x \in D$ , let

$$\begin{aligned}
& \rho_{n\beta}(D, x) \\
& \equiv \mu(\{\varepsilon | n\beta \cdot p_d(x) + \varepsilon(x) \geq \max_{y \in D \setminus x} \{n\beta \cdot p_d(y) + \varepsilon(y)\}\}) \\
& \geq \mu(\{\varepsilon | n\beta \cdot p_d(x) + \varepsilon(x) \geq \max_{y \in D \setminus x} n\beta \cdot p_d(y) + \max_{y \in D \setminus x} \varepsilon(y)\}) \\
& = \mu(\{\varepsilon | n(\beta \cdot p_d(x) - \max_{y \in D \setminus x} \beta \cdot p_d(y)) \geq \max_{y \in D \setminus x} \varepsilon(y) - \varepsilon(x)\}) \\
& = \int 1\{n(\beta \cdot p_d(x) - \max_{y \in D \setminus x} \beta \cdot p_d(y)) \geq \max_{y \in D \setminus x} \varepsilon(y) - \varepsilon(x)\} d\mu,
\end{aligned}$$

where 1 is the indicator function. By the dominated convergence theorem,

$$\lim_{n \rightarrow \infty} \rho_{n\beta}(D, x) \geq \int \lim_n 1\{n(\beta \cdot p_d(x) - \max_{y \in D \setminus x} \beta \cdot p_d(y)) \geq \max_{y \in D \setminus x} \varepsilon(y) - \varepsilon(x)\} d\mu.$$

Now suppose that  $\pi(x) > \pi(y)$  for all  $y \in D \setminus \{x\}$ , then  $\beta \cdot p_d(x) - \max_{y \in D \setminus x} \beta \cdot p_d(y) > 0$ . Thus for any given value of  $\varepsilon$ , the indicator function is one. It follows that  $\lim_{n \rightarrow \infty} \rho_{n\beta}(D, x) = 1$ . By taking a complement, if  $\pi(x) < \pi(D \setminus \{x\})$ , then  $\lim_{n \rightarrow \infty} \rho_{n\beta}(D, x) = 0$ . Hence,  $\rho_{n\beta} \rightarrow \rho^\pi$  as  $n \rightarrow \infty$ .  $\square$

*Step 2:* If there exists  $\mu \in \mathcal{M}$  and a sequence  $\{\rho_n\}$  of  $\mathcal{P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$ , then  $\pi$  is degree- $d$ -representable.

*Proof.* Let  $\beta_n$  be the coefficient vector of  $\rho_n$ . Consider a particular binary choice set  $\{x, y\}$ . Without loss of generality, assume  $\pi(x) > \pi(y)$ . We have  $\mu(\{\varepsilon | \beta_n \cdot p_d(x) + \varepsilon(x) > \beta_n \cdot p_d(y) + \varepsilon(y)\}) \rightarrow \rho^\pi(\{x, y\}, x) = 1$  as  $n \rightarrow \infty$ . This implies that there exists a  $N_{x,y}$  such that for all  $n \geq N_{x,y}$  we have  $\beta_n \cdot p_d(x) > \beta_n \cdot p_d(y)$ . To see this, suppose the previous claim is not true: we have a subsequence of  $n_k$  such that  $\beta_{n_k} \cdot p_d(x) \leq \beta_{n_k} \cdot p_d(y)$ . Then we must have  $\mu(\{\varepsilon | \beta_{n_k} \cdot p_d(x) + \varepsilon(x) > \beta_{n_k} \cdot p_d(y) + \varepsilon(y)\}) = 1 - \mu(\{\varepsilon | \beta_{n_k} \cdot p_d(x) - \beta_{n_k} \cdot p_d(y) \leq \varepsilon(y) - \varepsilon(x)\}) \leq 1 - \mu(\{\varepsilon | 0 < \varepsilon(y) - \varepsilon(x)\}) < 1$  uniformly in  $n_k$ . This contradicts with our hypothesis that  $\rho_n \rightarrow \rho^\pi$ . Finally, although  $N_{x,y}$  depend on a particular binary choice sets, we have a finite number of binary choice sets. Taking the maximum of  $N_{x,y}$  among all binary choice sets we have the desired result.  $\square$

*Step 3:* If there exists  $\mu \in \mathcal{M}$  and a sequence  $\{\rho_n\}$  of  $\text{co.}\mathcal{P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$ , then there exists a sequence  $\{\rho'_n\}$  of  $\mathcal{P}_a(d, 0|\mu)$  such that  $\rho'_n \rightarrow \rho^\pi$ .

*Proof.* Fix a positive integer  $d$  and  $\pi \in \Pi$ . Suppose that there exists a sequence  $\rho_n$  of  $\text{co.}\mathcal{P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$  as  $n \rightarrow \infty$ . Let  $M = \dim \text{co.}\mathcal{P}_a(d, 0|\mu)$ . Then for each  $\rho_n$ , by Caratheodory's theorem, there exist  $\{\rho_n^i\}_{i=1}^{M+1} \subset \mathcal{P}_a(d, 0|\mu)$  and nonnegative numbers  $\{\alpha_n^i\}_{i=1}^{M+1}$  such that  $\rho_n = \sum_{i=1}^{M+1} \alpha_n^i \rho_n^i$  and  $\sum_{i=1}^{M+1} \alpha_n^i = 1$ .



Denote  $(\alpha_n^i)_{i=1}^{M+1}$  by  $\alpha_n$ . Then  $\alpha_n$  belongs to a compact set (i.e.,  $M$ -dimensional simplex). There exists a convergent subsequence  $\{\alpha_{n'}\}$ . Thus  $\rho'_n \equiv \sum_{i=1}^{M+1} \alpha_{n'}^i \rho_{n'}^i$  is a subsequence of  $\{\rho_n\}$ . For each  $i$ , let  $\alpha_*^i$  be the limit of  $\{\alpha_{n'}^i\}$ . Since  $\sum_{i=1}^{M+1} \alpha_{n'}^i = 1$  for all  $n'$ , we have  $\sum_{i=1}^{M+1} \alpha_*^i = 1$ , so that there must exist  $i^*$  such that  $\alpha_*^{i^*} \neq 0$ .

In the following, we will show that  $\rho_{n'}^{i^*} \rightarrow \rho^\pi$  as  $n' \rightarrow \infty$ . To show the claim, we prove that if  $\rho_{n'}^{i^*} \not\rightarrow \rho^\pi$ , then  $\alpha_{n'}^{i^*} \rightarrow 0$ , which is a contradiction. Assume that  $\rho_{n'}^{i^*} \not\rightarrow \rho^\pi$ . Then there exist  $D \in \mathcal{D}$ ,  $x \in D$ , and  $\varepsilon > 0$  such that for any integer  $N$  there exists  $n > N$  such that  $|\rho_{n'}^{i^*}(D, x) - \rho^\pi(D, x)| > \varepsilon$ . This implies that for any  $N$  there exists  $n > N$  such that  $\left| \sum_{i=1}^{M+1} \alpha_{n'}^i \rho_{n'}^i(D, x) - \rho^\pi(D, x) \right| = \sum_{i=1}^{M+1} \alpha_{n'}^i |\rho_{n'}^i(D, x) - \rho^\pi(D, x)| \geq \alpha_{n'}^{i^*} \varepsilon$ , where the first equality holds because if  $\pi(x) \geq \pi(D)$  then  $\rho_{n'}^i(D, x) - \rho^\pi(D, x) \leq 0$  for all  $i$ ; if not  $\pi(x) \geq \pi(D)$  then  $\rho_{n'}^i(D, x) - \rho^\pi(D, x) \geq 0$  for all  $i$ . Since  $\sum_{i=1}^{M+1} \alpha_{n'}^i \rho_{n'}^i(D, x) \rightarrow \rho^\pi(D, x)$ , it must hold that  $\alpha_{n'}^{i^*} \rightarrow 0$ , which completes the proof of Step 3.  $\square$

Steps 2 and 3 show that if there exists a sequence  $\{\rho_n\}$  of  $\text{co.P}_a(d, 0|\mu)$  such that  $\rho_n \rightarrow \rho^\pi$ , then  $\pi$  is degree- $d$ -representable. The contraposition of this statement is the second statement of Lemma 2.

## B.5 Proof of Lemma 3

### B.5.1 Proof of Statement (1)

We use the following lemma:

**Lemma 6.** *Let  $A$  be an  $r \times n$  real matrix,  $B$  be an  $l \times n$  real matrix, and  $E$  be an real  $m \times n$  matrix. Exactly one of the following alternatives is true.*

1. *There is  $u \in \mathbf{R}^n$  such that  $Au = 0$ ,  $Bu \geq 0$ ,  $Eu \gg 0$ .*
2. *There is  $\theta \in \mathbf{R}^r$ ,  $\eta \in \mathbf{R}^l$ , and  $\pi \in \mathbf{R}^m$  such that  $\theta A + \eta B + \lambda E = 0$ ,  $\lambda > 0$  and  $\eta \geq 0$ ,*

*where  $\gg 0$  means all entries are positive,  $> 0$  means all entries are nonnegative and positive for some entry, and  $\geq$  means all entries are nonnegative.*

See Theorem 1.6.1 of Stoer and Witzgall (2012) for the proof. In the following by using Lemma 6, we prove statement (i).

For any ranking  $\pi \in \Pi$  and a positive integer  $d$ , consider the following condition: if  $\lambda_1 p_d(\pi^{-1}(|X|)) + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) p_d(\pi^{-1}(|X| + 1 - i)) - \lambda_{|X|-1} p_d(\pi^{-1}(1)) = 0$

and  $\lambda_i \geq 0$  for all  $i \in \{1, \dots, |X| - 1\}$ , then  $\lambda_i = 0$  for all  $i \in \{1, \dots, |X| - 1\}$ . We call this Condition (\*).

*Step 1:* For each  $\pi \in \Pi$  and a positive integer  $d$ , Condition (\*) holds if and only if  $\pi$  is degree- $d$ -representable.

*Proof.* Since  $\mathcal{D}$  contains all binary sets,  $\pi \in \Pi$  is representable if and only if there exists  $\beta$  such that for any  $x, y \in X$ ,  $\pi(x) > \pi(y) \Leftrightarrow \beta \cdot x > \beta \cdot y$ . Fix  $\pi \in \Pi$ .

$$\begin{aligned}
& \exists \beta [\beta \cdot p_d(\pi^{-1}(|X|)) > \beta \cdot p_d(\pi^{-1}(|X| - 1)) > \dots > \beta \cdot p_d(\pi^{-1}(2)) > \beta \cdot p_d(\pi^{-1}(1))] \\
& \Leftrightarrow \exists \beta [\beta \cdot (p_d(\pi^{-1}(|X|)) - p_d(\pi^{-1}(|X| - 1))) > 0, \dots, \beta \cdot (p_d(\pi^{-1}(2)) - p_d(\pi^{-1}(1))) > 0] \\
& \Leftrightarrow \exists \beta [E\beta \gg 0] \\
& \Leftrightarrow \exists \lambda \in \mathbf{R}^{|X|-1} [\lambda > 0, \lambda E = 0] \\
& \Leftrightarrow \exists \lambda \in \mathbf{R}^{|X|-1} [\lambda > 0, \sum_{i=1}^{|X|-1} \lambda_i (p_d(\pi^{-1}(|X| + 1 - i)) - p_d(\pi^{-1}(|X| - i))) = 0] \\
& \Leftrightarrow \exists \lambda \in \mathbf{R}^{|X|-1} [\lambda > 0, \\
& \quad \lambda_1 p_d(\pi^{-1}(|X|)) + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) p_d(\pi^{-1}(|X| + 1 - i)) - \lambda_{|X|-1} p_d(\pi^{-1}(1)) = 0] \\
& \Leftrightarrow \text{Condition}(*),
\end{aligned}$$

where  $\lambda \equiv (\lambda_1, \dots, \lambda_{|X|-1})$  and the third equivalence is obtained by using Lemma 6 with  $A, B = 0$  and  $E^\top \equiv (p_d(\pi^{-1}(|X|)) - p_d(\pi^{-1}(|X| - 1)), \dots, p_d(\pi^{-1}(2)) - p_d(\pi^{-1}(1)))$ .  $\square$

*Step 2:* For a given positive integer  $d$ , the set  $\{p_d(x) | x \in X\}$  is affinely independent if and only if Condition (\*) holds for  $d$  and any  $\pi \in \Pi$ .

*Proof.* We first show that the only if part. Fix any  $\pi \in \Pi$ . Without loss of generality assume that  $\pi(x_i) = |X| + 1 - i$  for all  $i \in \{1, \dots, |X|\}$ . Suppose that  $\lambda_1 p_d(\pi^{-1}(|X|)) + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) p_d(\pi^{-1}(|X| + 1 - i)) - \lambda_{|X|-1} p_d(\pi^{-1}(1)) = 0$  and  $\lambda_i \geq 0$  for all  $i$ . Then,  $\lambda_1 p_d(x_1) + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) p_d(x_i) - \lambda_{|X|-1} p_d(x_{|X|}) = 0$ . Define  $\mu_1 = \lambda_1$ ,  $\mu_i = \lambda_i - \lambda_{i-1}$  for all  $i \in \{2, \dots, |X| - 1\}$ , and  $\mu_{|X|} = -\lambda_{|X|-1}$ . Then  $\sum_{i=1}^{|X|} \mu_i p_d(x_i) = 0$ . Moreover,  $\sum_{i=1}^{|X|} \mu_i = \lambda_1 + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) - \lambda_{|X|-1} = 0$ . If  $\{p_d(x) | x \in X\}$  is affinely independent, then  $\mu_i = 0$  for all  $i \in \{1, \dots, |X|\}$ . Hence,  $\lambda_i = 0$  for all  $i \in \{1, \dots, |X| - 1\}$ . This implies Condition (\*).

Next we will show the if part. Choose any real numbers  $\{\mu_i\}_{i=1}^{|X|}$  such that  $\sum_{i=1}^{|X|} \mu_i p_d(x_i) = 0$  and  $\sum_{i=1}^{|X|} \mu_i = 0$  to show  $\mu_i = 0$  for all  $i \in \{1, \dots, |X|\}$ . Without loss of generality, order  $\mu_i$  by its value so that  $\mu_1 \geq \mu_2 \geq \dots \geq \mu_{|X|}$ . Let  $\mu \equiv (\mu_1, \dots, \mu_{|X|})$ . For each  $x_i \in X$ , define  $\pi(x_i) = |X| + 1 - i$ . Then  $\pi \in \Pi$ . Define  $\lambda_1 = \mu_1$  and  $\lambda_i = \sum_{j=1}^i \mu_j$  for all  $i \in \{2, \dots, |X| - 1\}$ .

First we will show that  $\lambda_i \geq 0$  for all  $i \in \{1, \dots, |X| - 1\}$ . Suppose by way

of contradiction that  $\lambda_i < 0$  for some  $i \in \{1, \dots, |X| - 1\}$ . Then  $\mu_i < 0$  because  $\mu_1 \geq \dots \geq \mu_i$ . Since  $0 > \mu_i \geq \mu_j$  for all  $j \geq i$ , we have  $\sum_{j=i+1}^{|X|} \mu_j < 0$ . It follows that  $\sum_{j=1}^{|X|} \mu_j = \lambda_i + \sum_{j=i+1}^{|X|} \mu_j < 0$ . This contradicts that  $\sum_{j=1}^{|X|} \mu_j = 0$ . Therefore,  $\lambda_i \geq 0$  for all  $i \in \{1, \dots, |X| - 1\}$ .

In the following, we will show  $\mu = 0$  by using  $\lambda_i \geq 0$  for all  $i \in \{1, \dots, |X| - 1\}$ . Notice that  $\lambda_1 p_d(\pi^{-1}(|X|)) + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) p_d(\pi^{-1}(|X| + 1 - i)) - \lambda_{|X|-1} p_d(\pi^{-1}(1)) = \lambda_1 p_d(x_1) + \sum_{i=2}^{|X|-1} (\lambda_i - \lambda_{i-1}) p_d(x_i) - \lambda_{|X|-1} p_d(x_{|X|}) = \mu_1 p_d(x_1) + \sum_{i=2}^{|X|-1} \mu_i p_d(x_i) - \sum_{i=1}^{|X|-1} \mu_i p_d(x_{|X|}) = \sum_{i=1}^{|X|} \mu_i p_d(x_i) = 0$ , where the second to the last equality holds because  $\sum_{i=1}^{|X|} \mu_i = 0$ . Therefore, by Condition (\*),  $\lambda_i = 0$  for all  $i \in \{1, \dots, |X| - 1\}$ . This implies  $\mu = 0$ .  $\square$

### B.5.2 Proof of Statement (2)

For any  $x \in X$ ,  $p_d(x) \notin \text{co.}(\{p_d(y) | y \in X \setminus \{x\}\}) \Leftrightarrow p_d(x)$  is an extreme point of  $\text{co.}(\{p_d(y) | y \in X\}) \Leftrightarrow p_d(x)$  is an exposed point of  $\text{co.}(\{p_d(y) | y \in X\}) \Leftrightarrow \exists \beta \forall y \in X \setminus \{x\} [\beta \cdot p_d(x) > \beta \cdot p_d(y)] \Leftrightarrow$  all raking  $\pi$ , which best alternative is  $x$ , is degree- $d$ -representable. The first and third equivalences are by the definitions of extreme points and exposed points, respectively, while the second equivalence is by the fact that  $\text{co.}(\{p_d(y) | y \in X\})$  is a polytope.

## B.6 Proof of Lemma 5

Let  $|X| = n$  and write  $X = \{x_1, \dots, x_n\}$ . Let  $\pi_n$  be a ranking over  $X_n$  such that  $\pi_n(x_i) > \pi_n(x_{i+1})$  for any  $i \leq n - 1$ . We will prove that  $\rho^{\pi_n}$  and  $\rho^{\pi_n^-}$  are adjacent. In particular, we will find  $t_n \in \mathbf{R}^{\mathcal{D}_n \times X_n}$  such that  $\rho^{\pi_n} \cdot t_n = \rho^{\pi_n^-} \cdot t_n = 0$ , and  $\rho^{\sigma_n} \cdot t_n > 0$  for any  $\sigma_n \in \Pi_n \setminus \{\pi_n, \pi_n^-\}$ . The proof is by induction on  $n$ .

**Induction Base:** Let us consider the case of  $n = 3$ . For  $b > a > 0$ , let  $t_3(\{x_1, x_2\}, x_1) = a$ ,  $t_3(\{x_2, x_3\}, x_2) = -b$ ,  $t_3(\{x_1, x_3\}, x_1) = b - a$ , and  $t_3(\{x_1, x_2, x_3\}, x_2) = a + b$ . For all other  $(D, x) \in \mathcal{D} \times X$ ,  $t_3(D, x) = 0$ . Then  $t_3$  is defined on  $\mathcal{D} \times X$  and satisfies the conditions. By a direct calculation, it can be shown that  $\rho^{\pi_3} \cdot t_3 = \rho^{\pi_3^-} \cdot t_3 = 0$ , and  $\rho^{\sigma_3} \cdot t_3 > 0$  for any  $\sigma_3 \in \Pi_3 \setminus \{\pi_3, \pi_3^-\}$ .

Assume that  $n \geq 4$ . For each  $i$  such that  $3 \leq i \leq n$ , define  $X_i = \{x_1, x_2, \dots, x_i\}$  and let  $\Pi_i$  be the set of rankings over  $X_i$ . For each  $i$  such that  $3 \leq i \leq n - 1$ , let  $\mathcal{D}_i \subset 2^{X_i} \setminus \emptyset$  be such that (i)  $\mathcal{D}_i \subset \mathcal{D}_{i+1}$  and  $\mathcal{D}_n = \mathcal{D}$ ; (ii) for each  $i$ ,  $\{x, y\} \in \mathcal{D}_i$  and  $\{x, y, z\} \in \mathcal{D}_i$  for any  $x, y, z \in X_i$ .

**Induction Hypothesis:** Let  $\pi_{n-1}$  be the ranking over  $X_{n-1}$  such that  $\pi_{n-1}(x_i) >$

$\pi_{n-1}(x_{i+1})$  for any  $i \leq n-2$ . Suppose that there exists  $t_{n-1} \in \mathbf{R}^{\mathcal{D}_{n-1} \times X_{n-1}}$  such that  $\rho^{\pi_{n-1}} \cdot t_{n-1} = \rho^{\pi_{n-1}^-} \cdot t_{n-1} = 0$ , and  $\rho^{\sigma_{n-1}} \cdot t_{n-1} > 0$  for  $\sigma_{n-1} \in \Pi_{n-1} \setminus \{\pi_{n-1}, \pi_{n-1}^-\}$ . Choose a positive number  $\varepsilon_{n-1}$  such that  $0 < \varepsilon_{n-1} < \min_{\sigma_{n-1} \in \Pi_{n-1} \setminus \{\pi_{n-1}, \pi_{n-1}^-\}} \rho^{\sigma_{n-1}} \cdot t_{n-1}$ . We define  $t_n \in \mathbf{R}^{\mathcal{D}_n \times X_n}$  as follows: For each  $(D, x) \in \mathcal{D}_n \times X_n$

$$t_n(D, x) = \begin{cases} t_{n-1}(D, x) & \text{if } (D, x) \in (\mathcal{D}_{n-1} \times X_{n-1}) \setminus \{(\{x_1, x_2\}, x_1)\}, \\ t_{n-1}(D, x) + \varepsilon_{n-1} & \text{if } (D, x) = (\{x_1, x_2\}, x_1), \\ -\varepsilon_{n-1}/(n-1) & \text{if } (D, x) = (\{x_i, x_n\}, x_i) \text{ for some } i \in \{1, \dots, n-1\}, \\ 2\varepsilon_{n-1} & \text{if } (D, x) = (\{x_{n-2}, x_{n-1}, x_n\}, x_{n-1}), \\ 0 & \text{otherwise.} \end{cases}$$

It is clear that  $\rho^{\pi_n} \cdot t_n = \rho^{\pi_n^-} \cdot t_n = 0$ . Let  $\sigma_n \in \Pi_n \setminus \{\pi_n, \pi_n^-\}$ . Let  $j \in \{1, \dots, n\}$  be such that the element  $x_n$  be  $j$ th best element in  $\sigma_n$ . There exists  $\sigma_{n-1} \in \Pi_{n-1}$  such that the ranking  $\sigma_n$  can be written as  $(\sigma_{n-1}^{-1}(n-1), \dots, \sigma_{n-1}^{-1}(n-j-1), x_n, \sigma_{n-1}^{-1}(n-j), \dots, \sigma_{n-1}^{-1}(1))$  in decreasing order of the ranking if  $2 \leq j \leq n-1$ .<sup>37</sup>

First notice that by the definition of  $t_n$  and  $\rho^{\sigma_{n-1}} = \rho^{\sigma_n}$  on  $\{x_1, x_2\}$ ,  $\rho^{\sigma_n} \cdot t_n = \rho^{\sigma_{n-1}} \cdot t_{n-1} + \varepsilon_{n-1} \rho^{\sigma_{n-1}}(\{x_1, x_2\}, x_1) - \frac{\varepsilon_{n-1}}{n-1}(j-1) + 2\varepsilon_{n-1} \rho^{\sigma_n}(\{x_{n-2}, x_{n-1}, x_n\}, x_{n-1})$ , where the second term of the right hand side is  $(\varepsilon_{n-1}/(n-1))(j-1)$  since in  $\sigma_n$ , there are  $j-1$  elements that are better than  $n$ .

**Case 1:**  $\sigma_{n-1} = \pi_{n-1}$ . Note that  $\rho^{\sigma_{n-1}}(\{x_1, x_2\}, x_1) = \rho^{\pi_{n-1}}(\{x_1, x_2\}, x_1) = 1$ .<sup>38</sup> Also  $\rho^{\sigma_n}(\{x_{n-2}, x_{n-1}, x_n\}, x_{n-1}) = 0$  since  $\rho^{\sigma_n}$  coincide with  $\rho^{\sigma_{n-1}} = \rho^{\pi_{n-1}}$  on  $X_{n-1}$  and  $x_{n-2}$  is better than  $x_{n-1}$  in the ranking  $\pi_{n-1}$ . Thus,  $\rho^{\sigma_n} \cdot t_n = 0 + \varepsilon_{n-1} - \frac{\varepsilon_{n-1}}{n-1}(j-1) + 0 > 0$ , where the last inequality holds because  $j < n$ . (If  $j = n$ , then  $\sigma_{n-1} = \pi_{n-1}$  implies that  $\sigma_n = \pi_n$ , which is a contradiction.)

**Case 2:**  $\sigma_{n-1} = \pi_{n-1}^-$ . Note that  $\rho^{\sigma_{n-1}} \cdot t_{n-1} = \rho^{\pi_{n-1}^-} \cdot t_{n-1} = 0$  and  $\rho^{\sigma_{n-1}}(\{x_1, x_2\}, x_1) = \rho^{\pi_{n-1}^-}(\{x_1, x_2\}, x_1) = 0$ . Note also that  $\rho^{\sigma_n}(\{x_{n-2}, x_{n-1}, x_n\}, x_{n-1}) = 1$  since (i)  $\rho^{\sigma_n}(\{x_{n-2}, x_{n-1}, x_n\}, x_{n-2}) = 0$ ; (ii)  $\rho^{\sigma_n}(\{x_{n-2}, x_{n-1}, x_n\}, x_n) = 0$ . (i) holds because  $\sigma_{n-1} = \pi_{n-1}^-$  and (ii) holds because  $\sigma_n \neq \pi_n^-$  and  $\sigma_{n-1} = \pi_{n-1}^-$ . Thus,  $\rho^{\sigma_n} \cdot t_n = 0 + 0 - \frac{\varepsilon_{n-1}}{n-1}(j-1) + 2\varepsilon_{n-1} > 0$ .

**Case 3:**  $\sigma_{n-1} \notin \{\pi_{n-1}, \pi_{n-1}^-\}$ . Thus,  $\rho^{\sigma_n} \cdot t_n > \varepsilon_{n-1} - \frac{\varepsilon_{n-1}}{n-1}(j-1) \geq 0$ , where the first inequality holds by  $\rho^{\sigma_{n-1}} \cdot t_{n-1} > \varepsilon_{n-1}$  and the second inequality holds by

<sup>37</sup>If  $j = 1$ , then  $x_n$  is the best element in  $\sigma_n$ . If  $j = n$ , then  $x_n$  is the worst element in  $\sigma_n$ .

<sup>38</sup>Remember that  $\pi_{n-1}(x_i) > \pi_{n-1}(x_{i+1})$  for any  $i \leq n-1$

$j \leq n$ .

## B.7 Proof of Lemma 4

To prove the lemma, we prove the following lemmas. Fix a ranking  $\pi$  that is not degree- $d$ -representable. For any  $\alpha \in (0, 1)$ , define  $\rho_\alpha^\pi \equiv \alpha\rho^\pi + (1 - \alpha)\rho^{\pi^-}$ . We first will show statement (a) mentioned after Lemma 4 in Section 3.2.

**Lemma 7.** *Let  $\mu \in \mathcal{M}$ . For any  $\alpha \in (0, 1)$ ,  $\rho_\alpha^\pi \notin \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta|\mu)$ .*

**Proof.** Choose any  $x, y, z \in X$  such that  $\pi(x) > \pi(y) > \pi(z)$ . Suppose by way of contradiction that  $\rho_\alpha^\pi \in \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta|\mu)$ . This implies there exists  $\rho_n \in \bigcup_\eta \mathcal{P}_a(d, \eta|\mu)$  such that  $\rho_n \rightarrow \rho_\alpha^\pi$ . Let  $(\eta_n, \beta_n)$  be corresponding to  $\rho_n$ . Consider the sequence  $\{\beta_n \cdot (p_d(x) - p_d(y)) + \eta_n\}$ .

*Step 1:* There exists a convergent subsequence  $\{\beta_{n'} \cdot (p_d(x) - p_d(y)) + \eta_{n'}\}$ .

*Proof.* To see this notice the indices of the original sequence  $\beta_n \cdot (p_d(x) - p_d(y)) + \eta_n$  must be bounded. If not, for each large number  $N$ , there exists  $|\beta_n \cdot (p_d(x) - p_d(y)) + \eta_n| > N$  for some  $n$ . This implies  $\rho_n(\{x, y\}, x)$  will be close to either 0 or 1 infinitely often, violating the convergence assumption. Since  $\beta_n \cdot (p_d(x) - p_d(y)) + \eta_n$  lies in a bounded set, we can extract a convergent subsequence  $\{\beta_{n'} \cdot (p_d(x) - p_d(y)) + \eta_{n'}\}$ .  $\square$

Given Step 1, we fix one convergent subsequence  $\{\beta_{n'} \cdot (p_d(x) - p_d(y)) + \eta_{n'}\}$ . We consider corresponding stochastic choice functions  $\rho_{n'}$ . Note that, by definition,  $\lim_{n'} \rho_{n'} = \rho_\alpha^\pi$ . To make our notation simple, in the following, we write  $\rho_n$  and  $\beta_n$  instead of  $\rho_{n'}$  and  $\beta_{n'}$ .

For any  $s, t \in \{x, y, z\}$  and  $n \in N$ , define  $E_{n,st} = \{\varepsilon | \beta_n \cdot p_d(s) + \eta_n(s) + \varepsilon(s) > \beta_n \cdot p_d(t) + \eta_n(t) + \varepsilon(t)\}$ ;  $E_{st} = \{\varepsilon | \lim_n (\beta_n \cdot p_d(s) + \eta_n(s)) + \varepsilon(s) \geq \lim_n (\beta_n \cdot p_d(t) + \eta_n(t)) + \varepsilon(t)\}$ ; and  $E'_{st} = \{\varepsilon | \lim_n (\beta_n \cdot p_d(s) + \eta_n(s)) + \varepsilon(s) > \lim_n (\beta_n \cdot p_d(t) + \eta_n(t)) + \varepsilon(t)\}$ . Since  $\mu$  is absolutely continuous with respect to the Lebesgue measure,  $\mu\{\varepsilon | \lim_n (\beta_n \cdot p_d(x) + \eta_n(x)) + \varepsilon(x) = \lim_n (\beta_n \cdot p_d(y) + \eta_n(y)) + \varepsilon(y)\} = 0$ . Thus  $\mu(E_{st}) = \mu(E'_{st})$  and  $E_{st}$  is the event that alternative  $s$  is preferred to alternative  $t$  ignoring measure zero events.

*Step 2:* (i)  $E_{xy} = E_{xz}$  and  $E_{zy} = E_{zx}$  up to a measure zero set; (ii)  $\mu(E_{xy} \cap E_{xz}) = \alpha$  and  $\mu(E_{zy} \cap E_{zx}) = 1 - \alpha$ .

*Proof.* By Fatou's lemma  $\alpha = \rho_\alpha^\pi(\{x, y, z\}, x) = \limsup \rho_n(\{x, y, z\}, x) = \limsup \mu(E_{n,xy} \cap E_{n,xz}) \leq \mu(\limsup (E_{n,xy} \cap E_{n,xz})) = \mu(E_{xy} \cap E_{xz})$ . Moreover,  $\alpha = \rho_\alpha^\pi(\{x, y\}, x) = \liminf \mu(E_{n,xy}) \geq \mu(\liminf E_{n,xy})$ , where the inequality holds by

Fatou's lemma. By the definition that  $\liminf E_{n,xy} \equiv \bigcup_{n=1}^{\infty} \bigcap_{i=n}^{\infty} E_{n,xy}$ , we have  $\liminf E_{n,xy} \subset E_{xy}$  and  $E'_{xy} \subset \liminf E_{n,xy}$ . Since  $\mu(E'_{xy}) = \mu(E_{xy})$ , it follows that  $\alpha \geq \mu(\liminf E_{n,xy}) = \mu(E_{xy})$ . In the same way, we have  $\alpha \geq \mu(E_{xz})$ . Thus we have  $\mu(E_{xy} \cap E_{xz}) \geq \alpha \geq \mu(E_{xy}) = \mu(E_{xz})$ . It follows that  $E_{xy} = E_{xz}$  up to a measure zero set and  $\mu(E_{xy} \cap E_{xz}) = \alpha$ . By symmetry, we obtain  $E_{zy} = E_{zx}$  up to a measure zero set and  $\mu(E_{zy} \cap E_{zx}) = 1 - \alpha$ .  $\square$

Define  $A = \{\varepsilon | U(\varepsilon(x), \varepsilon(y), \varepsilon(z)) \geq c\}$  and  $B = \{\varepsilon | U(\varepsilon(x), \varepsilon(y), \varepsilon(z)) \leq c\}$ , where

$$U = \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \end{bmatrix}, \quad c = \begin{bmatrix} \lim(\beta_n \cdot (p_d(y) - p_d(x)) + \eta_n(y) - \eta_n(x)) \\ \lim(\beta_n \cdot (p_d(z) - p_d(y)) + \eta_n(z) - \eta_n(y)) \end{bmatrix}. \quad (8)$$

*Step 3:*  $\mu(A) = \alpha$ ,  $\mu(B) = 1 - \alpha$ , and  $\mu(A \cup B) = 1$ .

*Proof.* By Step 2,  $\mu(E_{xy} \cap E_{xz}) = \alpha$  and  $\mu(E_{zy} \cap E_{zx}) = 1 - \alpha$ . Remember  $E_{st}$  is the event that  $s$  is chosen over  $t$  in the binary set  $\{s, t\}$ . Notice  $E_{xy} \cap E_{xz}$  and  $E_{zy} \cap E_{zx}$  have measure zero intersections by the transitivity of rankings, so the two events partition the probability space (ignoring measure zero events).

Now notice that  $\alpha = \rho_{\alpha}^{\pi}(\{y, z\}, y) = \mu(E_{yz})$ . Since the event  $E_{yz}$  is incompatible with the event  $E_{zy} \cap E_{zx}$  it must completely lie within the event  $E_{xy} \cap E_{xz}$ . Moreover, since  $\mu(E_{yz}) = \alpha = \mu(E_{xy} \cap E_{xz})$ , the event  $E_{yz}$  coincides with the event  $E_{xy} \cap E_{xz}$  (ignoring measure zero events). Finally notice the event  $A$  is the intersection of  $E_{xy} \cap E_{xz}$  and  $E_{yz}$ , up to a measure zero events. Thus,  $\mu(A) = \alpha$ . In a similar way, we can show that  $\mu(B) = 1 - \alpha$ . Thus we have  $\mu(A \cup B) = 1$ .<sup>39</sup>  $\square$

Let  $f$  be a density function of  $\mu$ . Fix  $\varepsilon_a \in A \cap \{\varepsilon | f(\varepsilon) > 0\}$  and  $\varepsilon_b \in B \cap \{\varepsilon | f(\varepsilon) > 0\}$ . Define  $a \equiv U\varepsilon_a$  and  $b \equiv U\varepsilon_b$ . Without loss of generality, we suppose there does not exist  $t \in \mathbb{R}$  such that  $(a - c) = t(b - c)$ , where  $c$  is defined as in (8). This can be achieved by the open support condition.<sup>40</sup> For any  $\lambda \in (0, 1)$ , define  $\varepsilon_{\lambda} \equiv \lambda\varepsilon_a + (1 - \lambda)\varepsilon_b$ .

*Step 4:* There exists some  $\lambda^* \in (0, 1)$  such that  $\varepsilon_{\lambda^*} \notin A \cup B$ .

*Proof.* First notice that for any  $\lambda \in (0, 1)$ ,  $U\varepsilon_{\lambda} \neq c$ . This is because if  $U\varepsilon_{\lambda} = c$

<sup>39</sup>First we can show that notice that  $1 - \alpha = \rho_{\alpha}^{\pi}(\{x, y\}, y) = \mu(E_{yx})$ . Since the event  $E_{yx}$  is not compatible with the event  $E_{xy} \cap E_{xz}$ ,  $E_{yx}$  must coincide the event  $E_{zy} \cap E_{zx}$  (ignoring measure zero events). Finally notice that the event  $B$  is the intersection of  $E_{zy} \cap E_{zx}$  and  $E_{yx}$ , up to a measure zero events. Thus  $\mu(B) = 1 - \alpha$ .

<sup>40</sup>Notice first  $U$  has full column rank. If such  $t$  exists, we can perturb the points  $\varepsilon_a$  and  $\varepsilon_b$  so that such  $t$  does not exist.

for some  $\lambda$ , then  $U\varepsilon_\lambda = \lambda U\varepsilon_a + (1 - \lambda)U\varepsilon_b = \lambda a + (1 - \lambda)b = c$  implies  $\lambda(a - c) = -(1 - \lambda)(b - c)$ , which contradicts the non existence of  $t$  above. By the above argument, to show Step 4, it suffices to prove that there exists some  $\lambda^* \in (0, 1)$  such that  $\varepsilon_{\lambda^*} \notin A' \cup B'$ , where  $A' = \{\varepsilon | U(\varepsilon(x), \varepsilon(y), \varepsilon(z)) > c\}$  and  $B' = \{\varepsilon | U(\varepsilon(x), \varepsilon(y), \varepsilon(z)) < c\}$ , where  $U$  and  $c$  are defined as in (8).

Suppose by way of contradiction that the desired  $\lambda^*$  does not exist. Then, this implies  $\{\varepsilon_\lambda\}_{\lambda \in (0,1)} \subset A' \cup B'$ , which is a contradiction. This is because the set  $\{\varepsilon_\lambda\}_{\lambda \in (0,1)}$  is connected, and  $A'$  and  $B'$  are disjoint open sets.  $\square$

Since  $\{\varepsilon | f(\varepsilon) > 0\}$  is convex,  $\varepsilon_{\lambda^*} \in \{\varepsilon | f(\varepsilon) > 0\}$ . Moreover,  $\{\varepsilon | f(\varepsilon) > 0\}$  is open and  $(A \cup B)^c$  is open, it follows from Step 4 that there exists an event around  $\varepsilon_{\lambda^*}$  that is outside  $A \cup B$  and is not measure zero. This contradicts with  $\mu(A \cup B) = 1$ .  $\blacksquare$

Given Lemma 7, in order to show Lemma 4, it suffices to show that even with using mixtures, it is impossible to approximate  $\rho_\alpha^\pi$ . For this purpose, we need two more lemma.

**Lemma 8.** (i) For any  $\rho \in \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$ , if  $\rho \notin \{\rho^\pi, \rho^{\pi^-}\}$  then  $\rho \notin \{\rho_\alpha^\pi | \alpha \in [0, 1]\}$ ; (ii) Let  $(t, a)$  be as in Definition 8 with a pair  $(\rho^\pi, \rho^{\pi^-})$  of adjacent rankings. For any  $\rho \in \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$ , if  $\rho \notin \{\rho^\pi, \rho^{\pi^-}\}$  then  $\rho \cdot t > a$ .

**Proof.** To show (i), suppose by way of contradiction that  $\rho \in \{\rho_\alpha^\pi | \alpha \in [0, 1]\}$ . Since  $\rho \notin \{\rho^\pi, \rho^{\pi^-}\}$ ,  $\rho = \rho_\alpha^\pi$  for some  $\alpha \in (0, 1)$ . By Lemma 7,  $\rho \notin \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$ , which is a contradiction.

Now we will show (ii) by using (i). Since  $\rho \in \mathcal{P}_r$ , it can be written as a convex combination of  $\rho^\pi$ 's:  $\rho = \sum_{\sigma \in \Pi} \mu(\sigma) \rho^\sigma = \mu(\pi) \rho^\pi + \mu(\pi^-) \rho^{\pi^-} + \sum_{\sigma \in \Pi \setminus \{\pi, \pi^-\}} \mu(\sigma) \rho^\sigma$ . By (i),  $\rho \in \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$  and  $\rho \notin \{\rho^\pi, \rho^{\pi^-}\}$  implies that  $\rho \notin \{\rho_\alpha^\pi | \alpha \in [0, 1]\}$ . Thus, we must have one of the  $\mu(\sigma)$  in the third term positive. Moreover, by definition and the fact that  $\rho^\pi$  and  $\rho^{\pi^-}$  are adjacent, for any  $\sigma \notin \{\pi, \pi^-\}$ ,  $\rho^\sigma \cdot t > a = \rho^\pi \cdot t = \rho^{\pi^-} \cdot t$ . Thus we can conclude that  $\rho \cdot t > a$ .  $\blacksquare$

**Lemma 9.** Let  $\mu \in \mathcal{M}$ . If there exists a sequence of degree- $d$  random-coefficient ARUMs with fixed effects  $\eta_n$  converging to  $\rho_\alpha^\pi$  for some  $\alpha \in (0, 1)$ , then there exists two sequences  $\rho_{(\eta_n, \beta_n)}$  and  $\rho_{(\eta_n, \beta_n^-)}$  of degree- $d$  ARUMs with fixed effects  $\eta_n$  that converges to  $\rho^\pi$  and  $\rho^{\pi^-}$ , respectively.

**Proof.** Since  $\bigcup_\eta \mathcal{P}_{ra}(d, \eta | \mu) = \bigcup_\eta \text{co.} \mathcal{P}_a(d, \eta | \mu)$ , there exists  $\sum_{i=1}^{M+1} \mu_n(i) \rho_{(\beta_n(i), \eta_n)} \rightarrow \rho_\alpha^\pi$ , where  $M = \dim \mathcal{P}_r + 1$  (allowing  $\mu_n(i) = 0$  for some  $i$ ). For all  $i$ , we first extract converging subsequences  $\mu_m(i)$  and  $\rho_{(\beta_m(i), \eta_m)}$  of  $\mu_n(i)$  and  $\rho_{(\beta_n(i), \eta_n)}$ , respectively.

We can do this sequentially. Notice that for each  $i$ ,  $\mu_m(i)$  is a bounded sequence in a compact set: thus, it has a convergent subsequence. We denote the limit by  $\mu^*(i)$ . Similarly,  $\rho_{(\beta_n(i), \eta_n)}$  belongs to a compact set of random utility models: thus it has a convergent subsequence. We denote the limit  $\rho^*(i)$ . A diagonal argument gives us desirable subsequences such that for all  $i$ ,  $\mu_m(i) \rightarrow \mu^*(i)$  and  $\rho_{(\beta_m(i), \eta_m)} \rightarrow \rho^*(i)$  as  $m \rightarrow \infty$ . Thus,  $\sum_i \mu_n(i) \rho_{(\beta_n(i), \eta_n)} \rightarrow \sum_i \mu^*(i) \rho^*(i) = \rho_\alpha^\pi$ . Moreover, since  $\rho_{(\beta_m(i), \eta_m)} \in \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$ , we have  $\rho^*(i) \in \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$ .

In the following, we will argue that there exists some  $i, j$  such that  $\rho^*(i) = \rho^\pi$  and  $\rho^*(j) = \rho^{\pi^-}$ . By way of contradiction and without loss of generality, suppose that  $\rho^*(i) \neq \rho^\pi$  for any  $i$ .<sup>41</sup>

Let  $(t, a)$  be as in Definition 8 with a pair  $(\rho^\pi, \rho^{\pi^-})$  of adjacent rankings.

We will consider two cases.

**Case 1:**  $\rho^*(i) \neq \rho^{\pi^-}$  for any  $i$ . For all  $i$ ,  $\rho^*(i) \in \text{cl.} \bigcup_\eta \mathcal{P}_a(d, \eta | \mu)$  and  $\rho^*(i) \notin \{\rho^\pi, \rho^{\pi^-}\}$ . Then, by Lemma 8 (ii),  $\rho^*(i) \cdot t > a$  for all  $i$ . Thus,  $\left(\sum_i \mu^*(i) \rho^*(i)\right) \cdot t = \sum_i \mu^*(i) \rho^*(i) \cdot t > a$ . On the other hand by Definition 8,  $\left(\sum_i \mu^*(i) \rho^*(i)\right) \cdot t = \rho_\alpha^\pi \cdot t = a$ . This is a contradiction.

**Case 2:**  $\rho^*(i) = \rho^{\pi^-}$  for some  $i$ . Define  $J = \{i \in \{1, \dots, M+1\} | \rho^*(i) = \rho^{\pi^-}\}$ . First notice that there exists  $i \in \{1, \dots, M+1\} \setminus J$  such that  $\mu^*(i) > 0$ . (If such  $i$  does not exist, then  $\rho^{\pi^-} = \sum_i \mu^*(i) \rho^*(i) = \rho_\alpha^\pi$ , which contradicts with  $\alpha \notin \{0, 1\}$ .) Then,  $a = \rho_\alpha^\pi \cdot t = \sum_i \mu^*(i) \rho^*(i) \cdot t = \sum_{i \in J} \mu^*(i) \rho^{\pi^-} \cdot t + \sum_{i \notin J} \mu^*(i) \rho^*(i) \cdot t > a$ , where the last inequality holds since as in Case 1, by Lemma 8 (ii),  $\rho^{\pi^-} \cdot t = a$  and  $\rho^*(i) \cdot t > a$  for all  $i \notin J$ . ■

### B.7.1 Main Proof of Lemma 4 by Using Lemma 7, 8, 9

As mentioned, given Lemma 7, it suffices to show that even with using mixtures, it is impossible to approximate  $\rho_\alpha^\pi$ .

Let  $\pi$  be a raking that is not degree- $d$ -representable. By Lemma 5,  $\rho^\pi$  and  $\rho^{\pi^-}$  are adjacent. Now suppose by way of contradiction that there exists a sequence of degree- $d$  ARUMS with fixed effects that approximates  $\rho_\alpha^\pi$  for some  $\alpha \in (0, 1)$ . Then by Lemma 9, there exist sequences  $\{(\eta_n, \beta_n, \beta'_n)\}$  such that (i)  $\rho_{(\eta_n, \beta_n)} \rightarrow \rho^\pi$  and (ii)  $\rho_{(\eta_n, \beta'_n)} \rightarrow \rho^{\pi^-}$ . Given (i), by exactly the same way as Step 2 of Lemma 2, we can prove that there exists large  $N_1$  such that for any  $n \geq N_1$ , we have  $\beta_n \cdot p_d(x) + \eta_n(x) > \beta_n \cdot p_d(y) + \eta_n(y)$  for any  $x, y \in X$  such that  $\pi(x) > \pi(y)$ . Similarly by (ii), there

<sup>41</sup>The proof for the other case is exactly the same after changing  $\rho^{\pi^-}$  to  $\rho^\pi$  and  $\rho^\pi$  to  $\rho^{\pi^-}$ .



exists large  $N_2$  such that for any  $n \geq N_2$ , we have  $\beta'_n \cdot p_d(x) + \eta_n(x) > \beta'_n \cdot p_d(y) + \eta_n(y)$  for any  $x, y \in X$  such that  $\pi^-(x) > \pi^-(y)$ .

Fix any  $x, y \in X$  such that  $\pi(x) > \pi(y)$ . Fix any number  $n_{x,y} \geq \max\{N_1, N_2\}$ . Then for any  $n \geq n_{x,y}$ , we have  $\beta_n \cdot p_d(x) + \eta_n(x) > \beta_n \cdot p_d(y) + \eta_n(y)$ . Since  $\pi^-(y) > \pi^-(x)$ , we have  $-\beta'_n \cdot p_d(x) - \eta_n(x) > -\beta'_n \cdot p_d(y) - \eta_n(y)$ . Summing the two inequalities, we have  $(\beta_n - \beta'_n) \cdot p_d(x) > (\beta_n - \beta'_n) \cdot p_d(y)$ . Because the number of binary choice sets is finite, we can find  $n^* > n_{x,y}$  for any  $x, y \in X$ . Thus, for any  $x, y \in X$  such that  $\pi(x) > \pi(y)$ , we have  $(\beta_{n^*} - \beta'_{n^*}) \cdot p_d(x) > (\beta_{n^*} - \beta'_{n^*}) \cdot p_d(y)$ . This contradicts with the fact that  $\pi$  is not degree- $d$ -representable.

## B.8 Proof of Proposition 4

To prove Proposition 4, we prove one lemma.

**Lemma 10.** *For any  $t \in \mathbf{R}^{\mathcal{D} \times X}$ ,  $\rho^\pi \cdot t = \rho^{\pi'} \cdot t$  for all  $\pi, \pi' \in \Pi$  if and only if  $t(D, x) = t(D, y)$  for all  $D \in \mathcal{D}$  and  $x, y \in D$ .<sup>42</sup>*

**Proof.** For notational convenience, for any  $\pi \in \Pi$  and  $D \in \mathcal{D}$  with  $D = \{x_1, \dots, x_{|D|}\}$ , we write  $\rho^\pi(D) = (\rho^\pi(D, x_1), \dots, \rho^\pi(D, x_{|D|}))$ . To prove the if part, assume  $t(D, x) = t(D, y)$  for all  $D \in \mathcal{D}$  and  $x, y \in D$ . Define  $t(D) = t(D, x)$  for any  $x \in D$ . Then for any  $\pi \in \Pi$ ,  $\rho^\pi \cdot t = \sum_{D \in \mathcal{D}} \sum_{x \in D} \rho^\pi(D, x) t(D, x) = \sum_{D \in \mathcal{D}} t(D) \sum_{x \in D} \rho^\pi(D, x) = \sum_{D \in \mathcal{D}} t(D)$ , completing the proof of the if part.

The only if part is obvious for any  $D$  such that  $|D| = 1$ . Consider any  $D$  such that  $|D| \geq 2$ . Let  $l$  be the maximal integer such that  $|D| \geq l + 1$  for any  $D \in \mathcal{D}$ . Then  $l \geq 1$ .<sup>43</sup>

*Claim:* For any  $D \in \mathcal{D}$  such that  $|D| = l + 1$  and any  $x, y \in D$ ,  $t(D, x) = t(D, y)$ .

*Proof.* To prove the claim, denote  $D$  by  $\{x, y, w_1, \dots, w_{l-1}\}$ . (If  $l \leq 1$ , then  $w_i$ 's are not included in  $D$  and remove  $w_i$ 's in the following proof.) Choose any  $\pi, \pi' \in \Pi$  such that for any  $z \in X \setminus \{x, y, w_1, \dots, w_{l-1}\}$  and any  $i \in \{1, \dots, l-1\}$ ,  $\pi(z) = \pi'(z)$ ,  $\pi(z) > \pi(x) > \pi(y) > \pi(w_i)$ ,  $\pi'(z) > \pi'(y) > \pi'(x) > \pi'(w_i)$ , and  $\pi(w_i) = \pi'(w_i)$ .

To show the claim, we will show the following two facts: (a) For any  $E \in \mathcal{D}$ ,  $\rho^\pi(E) \neq \rho^{\pi'}(E)$  if and only if  $\{x, y\} \subset E$  and  $\pi(x) \geq \pi(E)$ ; (b) If  $E \in \mathcal{D}$ ,  $\{x, y\} \subset E$  and  $\pi(x) \geq \pi(E)$ , then  $\rho^\pi(E, x) = 1$ ,  $\rho^\pi(E, z) = 0$  for any  $z \in E \setminus \{x\}$  and  $\rho^{\pi'}(E, y) = 1$ ,  $\rho^{\pi'}(E, z) = 0$  for any  $z \in E \setminus \{y\}$ .

<sup>42</sup>We are identifying each  $\rho \in \mathcal{P}$  as an element of  $\mathbf{R}^{\mathcal{D} \times X}$ .

<sup>43</sup>If  $\mathcal{D} = 2^X \setminus \emptyset$ , then  $l = 1$ . If  $\mathcal{D} \subsetneq 2^X \setminus \emptyset$ , then  $l$  can be larger than 1.

It is easy to see statement (b) and the only if part of statement (a). To show the if part of statement (a), assume  $\{x, y\} \not\subset E$  or  $\pi(x) < \pi(z)$  for some  $z \in E$ . First consider the case where  $\{x, y\} \not\subset E$ . If both  $x$  and  $y$  do not belong to  $E$ , then  $\rho^\pi(E) = \rho^{\pi'}(E)$  because the ranking over  $X \setminus \{x, y\}$  is the same for  $\pi$  and  $\pi'$ . If only one of them, say  $x$ , belongs to  $E$ , then  $\rho^\pi(E) = \rho^{\pi'}(E)$  because the ranking over  $X \setminus \{y\}$  is the same for  $\pi$  and  $\pi'$ .

Next consider the case where  $\pi(x) < \pi(z)$  for some  $z \in E$ . By the definition of  $\pi$ , we obtain  $z \in X \setminus \{x, y, w_1, \dots, w_{l-1}\}$ . Therefore,  $\pi'(y) < \pi'(z)$ . Hence,  $\rho^\pi(E, z) = 1 = \rho^{\pi'}(E, z)$  and  $\rho^\pi(E, z') = 0 = \rho^{\pi'}(E, z')$  for all  $z' \in E \setminus \{z\}$ .

Now, we will prove the claim. Since  $t \cdot \rho^\pi = t \cdot \rho^{\pi'}$ ,

$$\begin{aligned}
0 &= \sum_{(E,z) \in \mathcal{D} \times X} t(E, z) (\rho^\pi(E, z) - \rho^{\pi'}(E, z)) \\
&= \sum_{(E,z) \in \mathcal{D} \times X: \{x,y\} \subset E, \pi(x) \geq \pi(E)} t(E, z) (\rho^\pi(E, z) - \rho^{\pi'}(E, z)) & (\because \text{(a)}) \\
&= \sum_{E \in \mathcal{D}: \pi(x) \geq \pi(E), \{x,y\} \subset E} (t(E, x) - t(E, y)) & (\because \text{(b)}) \\
&= \sum_{E \in \mathcal{D}: \pi(x) \geq \pi(E), \{x,y\} \subset E, |E| \geq l+1} (t(E, x) - t(E, y)) \\
&\quad + \sum_{E \in \mathcal{D}: \pi(x) \geq \pi(E), \{x,y\} \subset E, |E| \leq l} (t(E, x) - t(E, y)) \\
&= t(D, x) - t(D, y) + \sum_{E \in \mathcal{D}: \pi(x) \geq \pi(E), \{x,y\} \subset E, |E| \leq l} (t(E, x) - t(E, y)),
\end{aligned}$$

where the last equality holds because if  $E$  contains both  $x$  and  $y$ ,  $\pi(x) \geq \pi(E)$ , and  $|E| \geq l+1$  then  $|E| = l+1$ , and hence  $E$  must be equal to  $D$ . The second term is zero because there is no  $D \in \mathcal{D}$  such that  $|D| \leq l$  by the definition of  $l$ . So  $t(D, x) = t(D, y)$ . This completes the proof of the claim.  $\square$

The general case can be proved by the induction on  $|D|$ . Choose any  $D$  such that  $|D| = l' + 1$ , where  $l' > l$ . Choose any  $x, y \in D$ . As an induction hypothesis, suppose that for any  $E \in \mathcal{D}$ , if  $|E| \leq l'$  then  $t(E, x) = t(E, y)$  for any  $x, y \in E$ . By the same argument (with  $l'$  in place of  $l$ ) in the proof of the claim, we have

$$0 = t(D, x) - t(D, y) + \sum_{E \in \mathcal{D}: \pi(x) \geq \pi(E), \{x,y\} \subset E, |E| \leq l'} (t(E, x) - t(E, y)).$$

Since the second term is zero by the induction hypothesis,  $t(D, x) = t(D, y)$ .  $\blacksquare$

### B.8.1 Main Proof of Proposition 4 by using Lemma 10

The set  $\{q \in \mathbf{R}^{\mathcal{D} \times X} | \text{(i) and (ii)}\}$  is affine. So it suffices to show that for any affine set  $A$ , if  $\mathcal{P}_r \subset A$ , then  $\{q \in \mathbf{R}^{\mathcal{D} \times X} | \text{(i) and (ii)}\} \subset A$ . Since the set is affine, then by Theorem 1.4 of Rockafellar (2015), there exist a positive integer  $L$ ,  $L \times (|\mathcal{D}| \times |X|)$

matrix  $B$ , and  $L \times 1$  vector  $b$  such that  $A = \{q \in \mathbf{R}^{\mathcal{D} \times X} | Bq = b\}$ . For any  $l \in \{1, \dots, L\}$ ,  $B_l(D, x)$  denotes  $(l, (D, x))$  entry of  $B$ . (Remember that  $B$  has a column vector for each  $(D, x) \in \mathcal{D} \times X$ .) So  $Bq = b$  means that for any  $l \in \{1, \dots, L\}$ ,

$$\sum_{D \in \mathcal{D}} \sum_{x \in X} B_l(D, x)q(D, x) = b_l. \quad (9)$$

By assuming  $\mathcal{P}_r \subset \{q \in \mathbf{R}^{\mathcal{D} \times X} | Bq = b\}$ , we will show that if  $q$  satisfies (i) and (ii), then (9) holds for any  $l \in \{1, \dots, L\}$ .

*Step 1:*  $B_l(D, x) = B_l(D, y)$  for any  $l \in \{1, \dots, L\}$ ,  $D \in \mathcal{D}$ , and  $x, y \in D$ . To prove Step 1, fix any  $l$ . For any  $\pi \in \Pi$ ,  $\rho^\pi \in \mathcal{P}_r \subset \{q \in \mathbf{R}^{\mathcal{D} \times X} | Bq = b\}$ . Hence, (9) holds with  $q = \rho^\pi$  for any  $\pi \in \Pi$ . Thus  $\rho^\pi \cdot B_l = \rho^{\pi'} \cdot B_l$  for any  $\pi, \pi' \in \Pi$ . By Lemma 10, this implies that  $B_l(D, x) = B_l(D, y)$  for any  $D \in \mathcal{D}$ , and  $x, y \in D$ .

By Step 1, we can define  $B_l(D) = B_l(D, x)$  for any  $x \in D$ .

*Step 2:* If  $q$  satisfies (i) and (ii), then  $Bq = b$ , i.e.,  $\sum_{D \in \mathcal{D}} \sum_{x \in X} B_l(D, x)q(D, x) = b_l$  for any  $l \in \{1, \dots, L\}$ . To prove Step 2, choose any  $\pi \in \Pi$  and  $l \in \{1, \dots, L\}$ . Since  $\rho^\pi \in \mathcal{P}_r \subset \{q \in \mathbf{R}^{\mathcal{D} \times X} | Bq = b\}$ , then by (9),

$$b_l = \sum_{D \in \mathcal{D}} \sum_{x \in X} B_l(D, x)\rho^\pi(D, x) = \sum_{D \in \mathcal{D}} B_l(D), \quad (10)$$

where the second equality holds by  $\rho^\pi(D, z) = 1$  if  $\pi(z) \geq \pi(D)$  and  $\rho^\pi(D, z) = 0$  otherwise.

Finally, by using these equalities, for each  $l \in \{1, \dots, L\}$ , we obtain the following equations:

$$\begin{aligned} \sum_{D \in \mathcal{D}} \sum_{z \in X} B_l(D, z)q(D, z) &= \sum_{D \in \mathcal{D}} \sum_{z \in D} B_l(D, z)q(D, z) \quad (\because \text{(ii)}) \\ &= \sum_{D \in \mathcal{D}} \sum_{z \in D} B_l(D)q(D, z) \quad (\because \text{Step 1}) \\ &= \sum_{D \in \mathcal{D}} B_l(D) \sum_{z \in D} q(D, z) \\ &= \sum_{D \in \mathcal{D}} B_l(D) \quad (\because \text{(i)}) \\ &= b_l. \quad (\because \text{(10)}) \end{aligned}$$

This establishes that  $\text{aff.}\mathcal{P}_r = \{q \in \mathbf{R}^{\mathcal{D} \times X} | \text{(i) and (ii)}\}$ .

The equalities in (i) and (ii) are independent. The dimension of  $\{q \in \mathbf{R}^{\mathcal{D} \times X} | \text{(ii)}\}$  is  $\sum_{D \in \mathcal{D}} |D|$ . The number of equalities of (i) is  $|\mathcal{D}|$ . Hence, the dimension of  $\mathcal{P}_r$  is  $(\sum_{D \in \mathcal{D}} |D|) - |\mathcal{D}| = \sum_{D \in \mathcal{D}} (|D| - 1)$ .

## B.9 Proof of Proposition 5

Since the set  $\text{cl.co.}\mathcal{P}_a(d, \eta|\mu)$  is compact and convex,  $\rho^* = \arg \inf_{\rho \in \text{cl.co.}\mathcal{P}_a(d, \eta|\mu)} d(\rho, \hat{\rho}) = \arg \inf_{\rho \in \text{cl.co.}\mathcal{P}_a(d, \eta|\mu)} \|\rho - \hat{\rho}\|_2^2$  exists and it can be written as a convex combination of elements of  $\text{cl.}\mathcal{P}_a(d, \eta|\mu)$ . By Caratheodory's theorem, it can be written as  $\rho^* = \sum_{i=1}^M \lambda_i \rho_i$ , where  $\lambda_i \geq 0$ ,  $\sum_i \lambda_i = 1$  and  $\rho_i \in \text{cl.}\mathcal{P}_a(d, \eta)$ ,  $M = \dim \mathcal{P}_r + 1$ . For each step  $n$ , define  $E_n = \|\hat{\rho} - \rho^n\|^2 - \|\hat{\rho} - \rho^*\|^2$ . For each step  $n$ , let  $\alpha_n^*$  and  $\rho_n^*$  be the minimizers over the grids  $\{\alpha_n\}$  and  $\text{cl.}\mathcal{P}_a(d, \eta|\mu)$ , respectively. Define  $C = \sum_i \lambda_i \|\rho_i - \rho^*\|^2$  and  $T = \max\{2E_1, 4C\}$ . Note that  $E_1$  can be upper bounded by  $2\|\hat{\rho}\|^2 + 2\|\rho^n\|^2 \leq 4|\mathcal{D}|$  and similarly  $C \leq 4|\mathcal{D}|$ . Thus we can choose  $T = 16|\mathcal{D}|$ .

Then, for each step  $n$  and each  $\alpha_n$ ,

$$E_n \leq (1 - \alpha_n)E_{n-1} + C\alpha_n^2. \quad (11)$$

In the following, we will show  $E_n \leq \frac{T}{n+1}$  for each  $n$ . We prove this by induction. The inequality holds with  $n = 1$ . Fix  $n$ . Suppose  $E_{n-1} \leq \frac{T}{n}$ . By substituting  $\alpha_n = \frac{2}{n+1}$  to (11), we have (i):  $E_n \leq \frac{T}{n+1}$ .<sup>44</sup> Let  $d^n = d(\hat{\rho}, \rho^n)$  and  $d^* = d(\hat{\rho}, \rho^*)$ . Since  $E_n = (\sum_{D \in \mathcal{D}} 1)^2 ((d^n)^2 - (d^*)^2)$ , we have (ii):  $(d^n)^2 - (d^*)^2 \leq \frac{T'}{n+1}$ , where  $T' = \frac{T}{(\sum_{D \in \mathcal{D}} 1)^2}$ . Then we have  $(d^n - d^*)^2 \leq (d^n - d^*)(d^n - d^*) + (d^n - d^*)2d^* = (d^n - d^*)(d^n + d^*) \leq \frac{T'}{n+1}$ , where we use the fact that  $d^n \geq d^*$  and  $d^* \geq 0$ . This implies  $d^n - d^* \leq \sqrt{\frac{T'}{n+1}}$ .<sup>45</sup>

$$\frac{44 E_n \leq \frac{n-1}{n+1} \frac{T}{n} + C \frac{4}{(n+1)^2} = \frac{(n^2-1)T + 4Cn}{(n+1)^2 n} \leq \frac{(n^2-1)T + Tn}{(n+1)^2 n} \leq \frac{n^2 T + Tn}{(n+1)^2 n} = \frac{Tn(n+1)}{(n+1)^2 n} = \frac{T}{n+1}.$$

<sup>45</sup>We comment that we can upper bound  $E_1$  and  $C$  by the squared diameter of the random utility polytope. For example  $C \leq \sum_i \lambda_i \|\rho_i - \rho^*\|^2 \leq \sup_{x, y \in \mathcal{P}_r} \|x - y\|_2^2 = 2 \times$  the number of choice sets. The extremum is achieved by selecting  $x$  to be a degenerate preference ranking and  $y$  its reverse ranking. Similarly we can bound  $E_1$ . Notice this implies  $T = 8 \times$  the number of choice sets. Thus  $T'$  should be

8  
the number of choice sets.

# Online Appendix for “Approximating Choice Data by Discrete Choice Models”

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## A Omitted Proofs

### A.1 Proof of Proposition 3

To prove the proposition, we will prove the following general claim. The claim is trivial when the set  $C$  is closed. Proposition 3 follows from the claim with  $C = \mathcal{P}_a$ , where  $\mathcal{P}_a$  may not be closed. (For example, when  $\mathcal{P}_a = \mathcal{P}_l$ )

*Claim:* For any set bounded  $C \subset \mathbf{R}^k$ , let  $\Delta(C)$  denote the set of Borel probability measures over  $C$ . Then,  $\text{co}.C = \{ \int x dm(x) | m \in \Delta(C) \}$ , where  $\int x dm(x)$  denotes  $k$ -dimensional vector whose  $l$ -th element is  $\int x(l) dm(x)$  for any  $l \in \{1, \dots, k\}$ .

*Proof.* By definition, we immediately obtain  $\text{co}.C \subset \{ \int x dm(x) | m \in \Delta(C) \}$ . In the following, we will show the statement (\*):  $\{ \int x dm(x) | m \in \Delta(C) \} \subset \text{co}.C$ . First we will show the statement (\*\*):  $\{ \int x dm(x) | m \in \Delta(C) \} \subset \text{cl.co}.C$ .

To prove this statement, suppose by way of contradiction that  $\int x dm(x) \notin \text{cl.co}.C$  for some  $m \in \Delta(C)$ . By the strict separating hyperplane theorem (Corollary 11.4.2 of Rockafellar (2015)), there exist  $t \in \mathbf{R}^k \setminus \{0\}$  and  $\alpha \in \mathbf{R}$  such that  $(\int x dm(x)) \cdot t = \alpha > x \cdot t$  for any  $x \in \text{cl.co}.C$ . This is a contradiction because  $\alpha = (\int x dm(x)) \cdot t = \int (x \cdot t) dm(x) < \int \alpha dm(x) = \alpha$ .

We now will show (\*) by the induction on the dimension of  $\text{co}.C$ .

**Induction Base:** If  $\dim \text{co}.C = 1$ , then there must exist  $y$  and  $z$  such that  $\text{co}.C$  is the line segment between  $y$  and  $z$ . In the following, we assume that the line segment does not contain both  $y$  and  $z$  but the proof for the other cases are similar. Then for any  $x \in C$ , there exists unique  $\alpha(x) \in (0, 1)$  such that  $x = \alpha(x)y + (1 - \alpha(x))z$ . Notice that the function  $\alpha$  is continuous in  $x$  and hence measurable. Moreover, the function  $\alpha$  is integrable because  $\alpha$  is bounded and nonnegative. Choose any  $m \in \Delta(C)$ , then  $\int \alpha dm = \int \alpha(x) dm(x)$  exists. Moreover, since  $0 < \alpha(x) < 1$ , it follows from the monotonicity of integral that  $0 < \int \alpha(x) dm(x) < 1$ . Denote the value of the integral by  $\beta \in (0, 1)$ . Then,  $\int x dm(x) = \int \alpha(x)y + (1 - \alpha(x))z dm(x) = \beta y + (1 - \beta)z \in \text{co}.C$ , as desired.

Choose any integer  $l \geq 3$ .

**Induction Hypothesis:** Now suppose that (\*) holds for any  $C$  such that  $\dim C \leq l$ .

**Induction Step:** For any  $C$  such that  $\dim C = l + 1$ , (\*) holds. To prove the step, choose any  $m \in \Delta(C)$ . By (\*\*), we have  $\int x dm(x) \in \text{cl.co.}C$ .

First consider the case where  $\int x dm(x) \in \text{rint.cl.co.}C$ . Since  $\text{rint.cl.co.}C = \text{rint.co.}C$  (by Theorem 6.3 of Rockafellar (2015)), we have  $\int x dm(x) \in \text{co.}C$ , as desired.

Next consider the case where  $\int x dm(x) \notin \text{rint.cl.co.}C$ . Then,  $\int x dm(x) \in \partial \text{cl.co.}C \equiv \text{cl.co.}C \setminus \text{rint.co.}C$ . By the strict separating hyperplane theorem (Corollary 11.4.2 of Rockafellar (2015)), there exists a supporting hyperplane  $H$  of  $\text{cl.co.}C$  at  $\int x dm(x)$ . There exist  $t \in \mathbf{R}^k \setminus \{0\}$  and  $\alpha \in \mathbf{R}$  such that  $H = \{x | x \cdot t = \alpha\}$  and  $\int x dm(x) \cdot t = \alpha > x \cdot t$  for any  $x \in \text{cl.co.}C \cap H^c$ . This implies that  $m(H) = 1$ . Hence,  $m(H \cap C) = 1$ . Since  $H$  is a supporting hyperplane and  $\text{cl.co.}C \not\subset H$ , we obtain  $\dim(H \cap \text{aff.}C) \leq l$ . Hence,  $\dim(H \cap C) \leq l$ . Therefore, the induction hypothesis shows that  $\int x dm(x) \in \text{co.}(H \cap C) \subset \text{co.}C$ , as desired.  $\square$

The claim above implies Proposition 3. The result is not true in an infinite dimensional space.<sup>46</sup>

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<sup>46</sup>Let  $\{e_i\}_{i=1}^{\infty}$  be the base of the infinite dimensional real space. Define  $C = \{e_i\}_{i=1}^{\infty}$ . Define a measure  $m$  on  $C$  such that  $m(e_i) = (1/2)^i$  for each  $i$ . Then,  $\sum_{i=1}^{\infty} m(e_i) = 1$ , so that  $m$  is a probability measure on  $C$ .  $\int x dm$  cannot be represented as any finite mixture of elements of  $C$ . For any  $y \in \text{co.}C$ , there exists  $i$  such that  $y(e_i) = 0$ .

## A.2 Derivation of (11) in Section 11

Full calculation is as follows:

$$\begin{aligned}
& E_n \\
&= \|\hat{\rho} - (1 - \alpha_n^*)\rho^{n-1} - \alpha_n^*\rho_n^*\|^2 - \|\hat{\rho} - \rho^*\|^2 \\
&\leq \sum_i \lambda_i \|\hat{\rho} - (1 - \alpha_n)\rho^{n-1} - \alpha_n\rho_i\|^2 - \|\hat{\rho} - \rho^*\|^2 \\
&= \sum_i \lambda_i \{(1 - \alpha_n)^2 \|\hat{\rho} - \rho^{n-1}\|^2 + 2\alpha_n(1 - \alpha_n)((\hat{\rho} - \rho^{n-1}) \cdot (\hat{\rho} - \rho_i)) + \alpha_n^2 \|\hat{\rho} - \rho_i\|^2\} \\
&\quad - \|\hat{\rho} - \rho^*\|^2 \\
&= (1 - \alpha_n)^2 \|\hat{\rho} - \rho^{n-1}\|^2 + 2\alpha_n(1 - \alpha_n)((\hat{\rho} - \rho^{n-1}) \cdot (\hat{\rho} - \sum_i \lambda_i \rho_i)) \\
&\quad + \alpha_n^2 \sum_i \lambda_i \|\hat{\rho} - \rho_i\|^2 - \|\hat{\rho} - \rho^*\|^2 \\
&\leq (1 - \alpha_n)^2 \|\hat{\rho} - \rho^{n-1}\|^2 + \alpha_n(1 - \alpha_n)(\|\hat{\rho} - \rho^{n-1}\|^2 + \|\hat{\rho} - \rho^*\|^2) - \|\hat{\rho} - \rho^*\|^2 \\
&\quad + \alpha_n^2 \sum_i \lambda_i \|\hat{\rho} - \rho_i\|^2 \\
&\leq (1 - \alpha_n)^2 \|\hat{\rho} - \rho^{n-1}\|^2 + \alpha_n(1 - \alpha_n)(\|\hat{\rho} - \rho^{n-1}\|^2 + \|\hat{\rho} - \rho^*\|^2) - \|\hat{\rho} - \rho^*\|^2 \\
&\quad + \alpha_n^2 \sum_i \lambda_i \|\rho_i - \rho^*\|^2 + \alpha_n^2 \|\rho^* - \hat{\rho}\|^2 \\
&= (1 - \alpha_n)\|\hat{\rho} - \rho^{n-1}\|^2 - (1 - \alpha_n)\|\hat{\rho} - \rho^*\|^2 + \alpha_n^2 \sum_i \lambda_i \|\rho_i - \rho^*\|^2 \\
&= (1 - \alpha_n)E_{n-1} + \alpha_n^2 \sum_i \lambda_i \|\rho_i - \rho^*\|^2.
\end{aligned}$$

## B EM Algorithm: Details

To compute approximation errors for degree-1-unrepresentable rankings in Table 1, we fit finite-mixture models to each deterministic preference ranking by the method of maximum likelihood. The data input is the observed stochastic choice function  $\hat{\rho}(D, x)$  and covariates of each alternative. We choose the number of mixtures,  $M$ , according to the theoretical upper bound using Corollary 2. Given the number of mixtures, the model has two sets of parameters: (1) mixture weights  $\{\lambda_i\}_{i=1}^M$  and (2) coefficients for each mixture  $\{\beta_i\}_{i=1}^M$ . The log-likelihood function of a finite mixture model with  $M$  mixtures is

$$\mathcal{L} \equiv \sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) \log \sum_{i=1}^M \lambda_i \frac{\exp(\beta_i \cdot x)}{\sum_{y \in D} \exp(\beta_i \cdot y)}.$$

We estimate the parameters by the EM algorithm (Dempster et al. (1977), Train (2009)). We implement the algorithm according to Chapter 14 in Train (2009). We terminate the algorithm when the change of the implied  $l_2$  distance between the estimated choice probability and the target choice probability is smaller than  $\frac{1}{10^6}$  between two successive runs.

Our use of Maximum Likelihood Estimation with the EM algorithm is partially motivated by the following observation: If the sufficient condition in Theorem 1-(i) is satisfied and the target choice probability is an interior random utility model  $\hat{\rho} \in \text{rint}.\mathcal{P}_r$ , then the model that maximizes the likelihood will yield a perfect fit to the target probability. Maximum Likelihood Estimation therefore minimizes the approximation error metric in (5).

To see this, notice that under the sufficient condition in Theorem 1-(i), Proposition 4 and Corollary 2 imply that any interior random utility model can be represented by a finite mixture of logit models with  $M = \sum_{D \in \mathcal{D}} (|D| - 1)$  mixtures. That is, there exists a set of parameters  $\{\beta_i^*, \lambda_i^*\}_{i=1}^M$  such that  $\sum_{i=1}^M \lambda_i^* \frac{\exp(\beta_i^* \cdot x)}{\sum_{y \in D} \exp(\beta_i^* \cdot y)} = \hat{\rho}(D, x)$  for any  $D \in \mathcal{D}$ ,  $x \in D$  and  $M = \sum_{D \in \mathcal{D}} (|D| - 1)$ . This set of parameters maximizes the likelihood. Recall that for any other choice probability vector  $\rho$ , the likelihood is:

$$\sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) \log(\rho(D, x)).$$

$\hat{\rho}$  maximizes the likelihood since

$$\begin{aligned} & \sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) (\log(\hat{\rho}(D, x)) - \log(\rho(D, x))) \\ &= \sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) \log \frac{\hat{\rho}(D, x)}{\rho(D, x)} \\ &= - \sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) \log \frac{\rho(D, x)}{\hat{\rho}(D, x)} \\ &\geq - \sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) \left( \frac{\rho(D, x)}{\hat{\rho}(D, x)} - 1 \right) \\ &= - \sum_{D \in \mathcal{D}} \sum_{x \in D} \rho(D, x) + \sum_{D \in \mathcal{D}} \sum_{x \in D} \hat{\rho}(D, x) = -|\mathcal{D}| + |\mathcal{D}| = 0, \end{aligned}$$

where we use the fact  $-\log(x) \geq -(x - 1)$  for the inequality. Finally observe that this set of parameters yields a perfect fit of the target probability.

## C In-sample and Out-of-sample Fit

In this section, we show that our method performs better or equally well compared to standard methods, not only in terms of in-sample fit but also in terms of out-of-sample fit. We use the same fishing choice dataset used in Section 5 and predict



choice probabilities using aggregated characteristics.

We estimate a random-coefficient logit model with arbitrary mixing distributions. In the dataset, we have four alternatives and we consider only one choice set  $\mathcal{D} = \{X\}$ . Thus by Proposition 4 and Corollary 2, it suffices to mix four logit models without fixed effects to represent any random utility model.<sup>47</sup> We also estimate several standard models for comparison. They include a multinomial logit model; a nested logit model with two nests (charter and the rest); a nested logit model with two nests (boat and the rest); a random coefficient logit model with a log-normal mixing distribution for each variable; a multinomial logit model with alternative fixed effects; and a random coefficient logit model with log-normal mixing distributions and alternative fixed effects. We detail the definition of each specification in Section C.1.

To evaluate in-sample and out-of-sample fit, we adopt the following strategy. We randomly divide individuals in the sample into a training sample and a test sample of equal sizes. Separately for the training and testing samples, we average individual choices and characteristics to obtain aggregate data on choice probabilities and characteristics. We then estimate the models using the training sample. The models are estimated by maximizing the log-likelihoods. That is, for each model, we solve the problem  $\max_{\theta \in \Theta} \sum_{j=1}^{|X|} \hat{\rho}_j \log \rho(x_j, \theta)$ , where  $j$  indexes fishing modes,  $\theta$  is the parameter vector of the model,  $\Theta$  denotes the set of possible parameter vectors,  $\hat{\rho}_j$  is the observed market share for fishing mode  $j$  in the training data, and  $\rho(x_j, \theta)$  is the model-predicted choice probability for fishing mode  $j$  with characteristic vector  $x_j$ . See Section C.1 for a likelihood expression for each model. For the standard models, we maximize the likelihoods with the nonlinear optimization package in R (Ghalanos and Theussl, 2015; Ye, 1987). For our model, we use the EM algorithm in Section B of Online Appendix.<sup>48</sup>

To evaluate the in-sample fit performance, we compute the predicted choice probabilities in the training sample ( $\hat{\rho}_{train} \in \mathbf{R}^{|X|}$ ) and compare it with the observed choice probabilities in the training sample ( $\rho_{train} \in \mathbf{R}^{|X|}$ ).<sup>49</sup> For this comparison, we calculate the  $l_2$  distance between the predicted choice probabilities and the aggregated observed choice probabilities  $\|\hat{\rho}_{train} - \rho_{train}\|_2$ . Similarly, to evaluate the out-of-sample performance, we compute the predicted choice probabilities using

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<sup>47</sup>In this case, it is easy to show mixing three logit models is enough.

<sup>48</sup>We prefer the EM algorithm over the greedy algorithm here because the EM algorithm is faster.

<sup>49</sup>We only consider the single choice set case in this simulation. So the choice probability vector has length  $|X|$ .

the testing sample ( $\hat{\rho}_{test} \in \mathbf{R}^{|X|}$ ) and compare it with the aggregated observed choice probabilities in the testing sample ( $\rho_{test} \in \mathbf{R}^{|X|}$ ). We use the  $l_2$  metric  $\|\hat{\rho}_{test} - \rho_{test}\|_2$  for this comparison as well.

We repeat this exercise with 50 random splits. The results for in-sample fits are reported in Table A.1. The results for out-of-sample fits are in Table A.2.

As expected, the in-sample fit of our model is perfect. Several standard models, especially those without fixed effects, exhibit imperfect in-sample fit. For example, the random coefficient logit model with the log normal distributions has the  $l_2$  prediction error 0.038.

Table A.2 shows that the out-of-sample prediction error of our model is positive but small. Standard models without alternative fixed effects have out-of-sample prediction errors substantially larger than our model. The two alternative models with fixed effects have out-of-sample prediction errors comparable to ours. This result suggests that even without using the fixed effects, our model performs better or equally well compared to standard models in this simulation, not only in terms of in-sample fit but also in terms of out-of-sample fit.

## C.1 Definitions of Other Models

In each of the standard models used in our empirical section, the choice probability  $\rho(X, j) \equiv \rho_j$  of alternative  $j$  from  $X$  is specified as follows:

- Multinomial logit:  $\rho_j = \frac{\exp(x'_j \beta)}{\sum_{j' \in J} \exp(x'_{j'} \beta)}$
- Nested logit (charter and others): the choice probability of alternative  $j$  that belongs to nest  $g$  is specified as

$$\rho_j = \frac{\exp(x'_j \beta / \lambda)}{\sum_{j' \in J_g} \exp(x'_{j'} \beta / \lambda)} \times \frac{\left[ \sum_{j' \in J_g} \exp(x'_{j'} \beta / \lambda) \right]^\lambda}{\sum_{g' \in G} \left[ \sum_{j' \in J_{g'}} \exp(x'_{j'} \beta / \lambda) \right]^\lambda}.$$

The nest is defined by the partition  $G = \{\{\text{charter}\}, \{\text{beach, boat, pier}\}\}$ .

- Nested logit (boat and others): the nested logit model specified above, with the nest defined by  $G = \{\{\text{boat}\}, \{\text{beach, charter, pier}\}\}$ .
- Mixed logit:  $\rho_j = \int \frac{\exp(x'_j \beta)}{\sum_{j' \in J} \exp(x'_{j'} \beta)} f(\beta) d\beta$  where  $f$  is the density of the distribution of random coefficients. We use independent log-normal distributions

Table A.1: In-Sample Fit

(1)	Choice probabilities				Prediction error
	Beach (2)	Boat (3)	Charter (4)	Pier (5)	(6)
Our method	0.114 (0.009)	0.353 (0.015)	0.383 (0.017)	0.151 (0.010)	0.000 (0.000)
Multinomial logit	0.141 (0.007)	0.355 (0.015)	0.378 (0.017)	0.126 (0.007)	0.038 (0.009)
Nested logit (charter and others)	0.114 (0.010)	0.353 (0.015)	0.383 (0.017)	0.150 (0.011)	0.001 (0.002)
Nested logit (boat and others)	0.141 (0.007)	0.355 (0.015)	0.378 (0.017)	0.126 (0.007)	0.038 (0.009)
Mixed logit with log normal distribution	0.142 (0.008)	0.354 (0.015)	0.378 (0.017)	0.126 (0.007)	0.038 (0.009)
Multinomial logit with fixed effects	0.113 (0.009)	0.353 (0.015)	0.383 (0.017)	0.151 (0.010)	0.000 (0.000)
Mixed logit with log normal distribution and fixed effects	0.114 (0.009)	0.353 (0.015)	0.383 (0.017)	0.151 (0.010)	0.000 (0.000)

*Note:* Table A.1 summarizes the in-sample fit of different models. The row “our method” presents choice probabilities predicted by the four-mixture mixed logit model and the prediction error. The remaining rows present in-sample predicted choice probabilities and prediction errors obtained by standard models. In parentheses are standard deviations obtained by repeating the same analyses 50 times.

for each coefficient. To evaluate the integral, we random draw 100 realizations from the random coefficient distribution.

- Multinomial logit with fixed effects: the above multinomial logit model with  $x$  including dummies for each alternative (except for beach).
- Mixed logit with fixed effects: the random coefficient logit model with log normal distributions. We also include fixed effects for each alternative (except for beach). To evaluate the integral, we random draw 100 realizations from the random coefficient distribution.

Table A.2: Out-Sample Fit

(1)	Choice probabilities				Prediction error
	Beach (2)	Boat (3)	Charter (4)	Pier (5)	(6)
Our method	0.114 (0.009)	0.353 (0.015)	0.383 (0.017)	0.151 (0.010)	0.049 (0.017)
Multinomial logit	0.143 (0.011)	0.353 (0.017)	0.377 (0.022)	0.127 (0.011)	0.058 (0.019)
Nested logit (charter and others)	0.115 (0.012)	0.350 (0.022)	0.383 (0.018)	0.152 (0.014)	0.050 (0.020)
Nested logit (boat and others)	0.143 (0.011)	0.353 (0.017)	0.377 (0.022)	0.127 (0.011)	0.058 (0.019)
Mixed logit with log normal distribution	0.143 (0.010)	0.352 (0.016)	0.377 (0.021)	0.127 (0.010)	0.058 (0.018)
Multinomial logit with fixed effects	0.116 (0.014)	0.350 (0.019)	0.380 (0.022)	0.154 (0.019)	0.048 (0.022)
Mixed logit with log normal distribution and fixed effects	0.113 (0.008)	0.353 (0.015)	0.383 (0.018)	0.151 (0.010)	0.048 (0.017)

*Note:* Table A.2 summarizes the out-sample fit of different models. The row “our method” presents choice probabilities predicted by the four-mixture mixed logit model and the prediction error (5). The remaining rows present out-of-sample predicted choice probabilities and prediction errors obtained by standard models. In parentheses are standard deviations obtained by repeating the same analyses 50 times.