Identification and inference in discrete choice models with imperfect information*

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Abstract

We study identification and inference of preference parameters in a single-agent, static, discrete choice model where the decision maker may face attentional limits precluding her to exhaustively acquire information about the payoffs of the available alternatives. Instead of explicitly modelling the information constraints, which can be susceptible to misspecification, we leverage on the notion of one-player Bayesian Correlated Equilibrium in Bergemann and Morris (2016) to provide a tractable characterisation of the sharp identified set and discuss inference under minimal assumptions on the amount of information processed by the decision maker. Simulations reveal that the obtained bounds on the preference parameters can be tight in several settings of empirical interest.

Keywords: Discrete choice model, Bayesian Persuasion, Bayes Correlated Equilibrium, Incomplete Information, Partial Identification, Moment Inequalities.

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1 Introduction

Attentional limits have long been recognised to play a critical role in decision problems because they preclude agents' ability to exhaustively process information about the values of the available alternatives (e.g., Simon, 1955; 1959; Kaheman, 1973; Sims, 1998; 2003; 2006; Lacetera, Pope, and Sydnor, 2012; Des Los Santos, Hortaçsu, and Wildenbeest, 2012; Matějka and McKay, 2015; Caplin, Dean, and Leahy, 2019). In this paper we offer a robust and tractable method to incorporate attentional limits in the empirical analysis of decision problems. In particular, we study identification and inference of preferences in a single-agent, static, discrete choice model where the decision maker (hereafter, DM) may face attentional limits hampering her capacity to learn about the payoffs generated by the available alternatives.

More formally, we consider a static setting where the DM has to choose an alternative from a finite set. The payoff generated by each alternative depends on the state of the world.[1] The DM chooses an alternative without being fully aware about the state of the world. Instead, the DM has a prior about the state of the world. Moreover, the DM has the opportunity to investigate further the state of the world by processing additional information (hereafter, *information structure*). Such information structure takes the form of a noisy signal of the state of the world. Admissible information structures range from full revelation of the state of the world to no information whatsoever, depending on the DM's attentional limits. The DM uses the acquired information structure to update her prior and obtain a posterior. Finally, the DM chooses an alternative maximising the expected payoff, where the expectation is computed via the posterior.

We assume that the researcher has data on choices made by many i.i.d. DMs facing the decision problem above and, possibly, one some covariates which may or may not include the state of the world. However, the researcher does not observe information structures, which remain latent, potentially heterogenous across agents, and arbitrarily correlated with the payoff-relevant variables. Our objective is studying identification and inference of the preference parameters (specifically, payoff functions and distributions of unobservables) from the empirical choice probabilities, while remaining agnostic about information structures. We believe that performing this exercise is important for two reasons. First, recovering the preference parameters permits us to obtain (bounds for) counterfactual choice probabilities when the researcher changes some payoff-relevant variables but keeps information structures the same (Bergemann, Brooks, and Morris, 2019). If the researcher is more informed than agents about the state of the world, it permits us also to obtain (bounds for) counterfactual choice probabilities when the researcher modifies information structures but keeps payoff-relevant variables the same. Second, leaving information structures completely unrestricted means that our results are robust to various assumptions which could be imposed on agents' cognitive skills. In

[1]The state of the world is defined by the realisation of variables like attributes of the available alternatives, attributes and tastes of the DM, exogenous market shocks, etc.

fact, the developed framework nests several discrete choice models that have been analysed in the literature, e.g., Logit model, Nested Logit model, Mixed Logit model, discrete choice models with rational inattention (e.g., Caplin and Dean, 2015; Matějka and McKay, 2015), some discrete choice models with search (e.g., Hébert and Woodford, 2018; Morris and Strack, 2019), and discrete choice models with risk aversion (see Barseghyan, Molinari, O'Donoghue, and Teitelbaum, 2018 for a review).

Studying identification and inference of the preference parameters while remaining agnostic about information structures is challenging because the model is incomplete in the sense of Tamer (2003), thus raising the possibility of partially identified preference parameters. Tractably characterising the sharp identified set is not an easy task. In fact, in order to determine whether a given parameter value belongs to the sharp identified set, we need to establish whether the empirical choice probabilities belong to the collection of choice probabilities predicted by our model under a range of possible information structures. The difficulty here lies in the necessity of exploring all possible information structures.

We approach the above problem by applying the notion of one-player Bayes Correlated Equilibrium provided in Bergemann and Morris (2013; 2016).[2] Specifically, we exploit Theorem 1 in Bergemann and Morris (2016) to claim that the collection of choice probabilities predicted by our model under a range of possible information structures is equivalent to the collection of choice probabilities predicted by our model under the notion of one-player Bayes Correlated Equilibrium. That is, it is equivalent to the collection of choice probabilities in a mediated decision problem where the mediator directly gives recommendations to the DMs and these recommendations are incentive compatible. Further, such a collection is a convex set. Therefore, determining whether a given parameter value belongs to the sharp identified set amounts to finding whether the empirical choice probabilities belong to that convex set. By using insights from Magnolfi and Roncoroni (2017) and Syrgkanis, Tamer, and Ziani (2018), we argue that this corresponds to solving a linear programming problem. Thus, constructing the sharp identified set becomes a computationally tractable exercise. Lastly, after having reformulated the identifying restrictions as moment inequalities, we explain how inference on the sharp identified set can be conducted by using Andrews and Shi (2013)'s generalised moment selection procedure. Simulations of discrete choice models with risk aversion and Nested Logit models highlight that our methodology can produce informative bounds for the preference parameters.

Research questions similar to ours have been addressed in the literature using different approaches. Caplin and Martin (2015) study a related problem by using data on choices for every possible realisation of the state of the world. These data are available, for example, through lab experiments. Instead, in our framework the researcher may or may not observe

[2]Note that the notion of one-player Bayes Correlated Equilibrium can be related to Bayesian Persuasion (Kamenica and Gentzkow, 2011). Further, Caplin and Martin (2015) discusses the relation between one-player Bayes Correlated Equilibrium, Bayesian Persuasion, and Bayesian Expected Utility maximisation.

the state of the world.

Another approach consists in modelling the mechanism according to which agents acquire information structures. By doing so, the analyst may obtain point identification of the preference parameters, however at the cost of potential misspecification of information constraints. For example, Mehta, Rajiv, and Srinivasan (2003), Honka and Chintagunta (2016), and Abaluck and Compiani (2019) consider search frameworks, where agents follow a protocol to learn about payoffs. Csaba (2018) adopts a rational inattention perspective, where the attentional costs sustained by agents to acquire information structures are parametrically modelled, along the lines of Caplin and Dean (2015), Matějka and McKay (2015), Fosgerau, Melo, de Palma, and Shum (2017), and Caplin, Dean, and Leahy (2019).

Further, this paper broadly relates to the econometric literature on discrete choice models when the sets of alternatives actually considered by agents (hereafter, *consideration sets*) could be subsets of the entire set of alternatives, heterogenous, arbitrarily correlated with the payoff-relevant variables, and latent (for some recent contributions see, e.g., Abaluck and Adams, 2018; Barseghyan, Coughlin, Molinari, and Teitelbaum, 2019; Barseghyan, Molinari, and Thirkettle, 2019; Cattaneo, Ma, Masatlioglu, and Suleymanov, 2019). In fact, one key implication of attentional limits is that, since attention is a scarce resource, agents may process information structures inducing them to contemplate, in equilibrium, only a subset of the available alternatives, ignoring all the others. Hence, in our model, consideration sets can arise endogenously (Caplin, Dean, and Leahy, 2019).[3,4] Yet, there is an important difference between the literature on the econometrics of consideration sets and this paper. The former focuses on recovering consideration probabilities for alternatives from the empirical choice probabilities. The latter studies the complementary problem of imperfect information at the level of payoffs. Thus, our methodology permits us to make counterfactual predictions when the analyst changes some payoff-relevant variables but keeps information structures the same, or when the analyst modifies information structures but keeps payoff-relevant variables the same.

More generally, this work also relates to the literature on relaxing assumptions about expectation formation and about the amount of information on which agents condition their expectations (see, e.g., the seminal paper by Manski, 2004). Our paper can be interpreted as a robustness exercise in that direction. In fact, by not restricting information structures, we allow agents to compute expectations with *any Bayes-plausible* posterior.

Lastly, this paper relates to two important works, Magnolfi and Roncoroni (2017) and

[3]Recall that the DM's information structure takes the form of a noisy signal of the state of the world. Hence, an alternative belongs to the DM's consideration set if the subset of the signal's support inducing the DM to choose that alternative has positive measure (Caplin, Dean, and Leahy, 2019). More details are in Section 2.

[4]Limited attention in choice is not the only mechanism that can induce endogenous considerations sets in discrete choice models. Consideration sets may arise also because of lack of awareness of some alternatives in the feasible set (e.g., Goeree, 2008), deliberately ignoring some alternatives in the feasible set (e.g., Wilson, 2008), incomplete product availability (e.g., Conlon and Mortimer, 2014), being offered the possibility of receiving program access from outside an experiment (e.g., Kamat, 2019), and absence of market clearing transfers in two-sided matching models (e.g., He, Sinha, and Sun, 2019).

Syrgkanis, Tamer, and Ziani (2018), that exploit Theorem 1 in Bergemann and Morris (2016) to characterise the sharp identified set in an entry game framework and in an auction framework, respectively, under latent information structures. Despite relying on a similar technology, our framework is not nested in theirs because, first, we consider a multinomial choice setting. Second, we impose different assumptions on agents' minimal amount of information. In particular, in our framework agents are uncertain about their own payoffs, while in Magnolfi and Roncoroni (2017) and Syrgkanis, Tamer, and Ziani (2018) agents are uncertain about others' payoffs. We contribute to this thread of the literature by highlighting the empirical usefulness of the notion of Bayes Correlated Equilibrium in a single-agent, static, discrete choice model with attentional limits.

The remainder of the paper is organised as follows. Section 2 describes the model. Section 3 discusses identification. Section 4 presents examples and simulations. Section 5 illustrates inference. Section 6 concludes.

Notation Capital letters are used for random variables/vectors/matrices and small case letters for their realisations. Calligraphic capital letters are used for sets. Given a random vector Z, P_Z denotes its joint density when all the components of Z are continuous, mixed joint density when some components of Z are continuous and some discrete, and probability mass function when all the components of Z are continuous. However, for readability, sometimes in the paper we generically refer to P_Z as a *density*.

$\mathbb{R}^K_+$ denotes the K-dimensional positive real space. Given set $\mathcal{A}$, $\Delta(\mathcal{A})$ is the function space of all possible densities with support equal to or contained in $\mathcal{A}$. Given set $\mathcal{A}$, $|\mathcal{A}|$ denotes $\mathcal{A}$'s cardinality. Given two sets, $\mathcal{A}$ and $\mathcal{R} \subseteq \mathcal{A}$, $\mathcal{A} \setminus \mathcal{R}$ is the complement of $\mathcal{R}$ in $\mathcal{A}$. 0_L is the $L \times 1$ vector of zeros.

Consider two random variables, Z and X, with supports $\mathcal{Z}$ and $\mathcal{X}$, respectively. Given $x \in \mathcal{X}$, we denote the density of Z conditional on $X = x$ by $P_{Z|X}(\cdot|x)$. Further, we denote the family of densities of Z conditional on every realisation x of X by $\mathcal{P}_{Z|X}$, i.e., $\mathcal{P}_{Z|X} \equiv \{P_{Z|X}(\cdot|x) \in \Delta(\mathcal{Z}) : x \in \mathcal{X}\}$. Note that $\mathcal{P}_{Z|X}$ contains $|\mathcal{X}|$ densities.

$\mathbb{S}^{|\mathcal{Y}|}$ is the unit sphere in $\mathbb{R}^{|\mathcal{Y}|}$, i.e., $\mathbb{S}^{|\mathcal{Y}|} \equiv \{b \in \mathbb{R}^{|\mathcal{Y}|} : b^T b = 1\}$. $\mathbb{B}^{|\mathcal{Y}|}$ is the unit ball in $\mathbb{R}^{|\mathcal{Y}|}$, i.e., $\mathbb{S}^{|\mathcal{Y}|} \equiv \{b \in \mathbb{R}^{|\mathcal{Y}|} : b^T b \leq 1\}$.

"$\times$" denotes the Cartesian product operator or is used to indicate vector dimensions. "$\cdot$" denotes the standard product operator.

2 The model

In this section we describe a single-agent, static, discrete choice model, where DM i may be partially informed about the payoffs generated by the available alternatives. Then, for any given amount of information processed by DM i, we characterise DM i's optimal strategy.

Let DM i face the decision problem of choosing an alternative from the finite set $\mathcal{Y}$ under incomplete information about the state of the world. The state of the world affects the payoff that DM i gets from the decision problem and is represented by a vector, (x_i, e_i, v_i). x_i is a realisation of some covariates, X_i, with finite support $\mathcal{X}$ and probability mass function P_X. x_i is observed by DM i and the researcher. e_i is a realisation of some tastes of DM i, ϵ_i, with finite support $\mathcal{E}$ and probability mass function conditional on $X_i = x_i$ denoted by $P_{\epsilon|X}(\cdot|x_i) \in \mathcal{P}_{\epsilon|X}$. e_i is observed by DM i but not by the researcher. v_i is a realisation of some further (dis)value, V_i, that DM i can derive from the choice problem, with finite support $\mathcal{V}$. v_i may or may not be observed by the researcher. v_i is not observed by DM i. However, DM i has a prior about V_i conditional on $(X_i, \epsilon_i) = (x_i, e_i)$, denoted by $P_{V|X,\epsilon}(\cdot|x_i, e_i) \in \mathcal{P}_{V|X,\epsilon}$.[5,6] Moreover, DM i can refine such a prior upon reception of a private signal, t_i, which may or may not be informative about v_i. For example, a firm can interview candidates to understand better their quality before hiring one of them. In particular, t_i is a realisation of the random variable (or, vector/matrix) T_i, with support $\mathcal{T}_i$ (not necessarily finite) and density conditional on $(X_i, \epsilon_i, V_i) = (x_i, e_i, v_i)$ denoted by $P^i_{T|X,\epsilon,V}(\cdot|x_i, e_i, v_i) \in \mathcal{P}^i_{T|X,\epsilon,V}$. DM i observes t_i, uses $P^i_{T|X,\epsilon,V}(\cdot|x_i, e_i, v_i)$ to update $P_{V|X,\epsilon}(\cdot|x_i, e_i)$, and obtains the posterior, $P^i_{V|X,\epsilon,T}(\cdot|x_i, e_i, t_i) \in \mathcal{P}^i_{V|X,\epsilon,T}$, via the Bayes rule. Finally, DM i chooses alternative $y \in \mathcal{Y}$ maximising her expected payoff, $\sum_{v\in\mathcal{V}} u(y, x_i, e_i, v) P^i_{V|X,\epsilon,T}(v|x_i, e_i, t_i)$, where $u : \mathcal{Y} \times \mathcal{X} \times \mathcal{E} \times \mathcal{V} \to \mathbb{R}$ is the payoff function. If there is more than one maximising alternative (i.e., if there are ties), then DM i applies some tie-breaking rule.

It is useful to summarise the framework above as follows. $G \equiv (\mathcal{Y}, \mathcal{X}, \mathcal{E}, \mathcal{V}, u, \mathcal{P}_{V|X,\epsilon}, \mathcal{P}_{\epsilon|X})$ will be hereafter called "*baseline choice problem*". G contains the primitives that the researcher wants to identify, i.e., u, $\mathcal{P}_{V|X,\epsilon}$, and $\mathcal{P}_{\epsilon|X}$. In the identification analysis, we will assume that G is the *minimal* amount of information available to DM i before choosing, together with (x_i, e_i). $S_i \equiv (\mathcal{T}_i, \mathcal{P}^i_{T|X,\epsilon,V})$ will be hereafter called DM i's "*information structure*". S_i represents the additional amount of information that DM i processes to form a posterior about V_i, together with t_i. S_i can range from complete revelation of V_i (hereafter, complete information structure[7]) to no information whatsoever on V_i (hereafter, degenerate information structure[8]), depending on DM i's attentional limits. In the identification analysis, we will treat S_i as unobserved by the researcher. Lastly, the pair (G, S_i) constitutes what will be hereafter called DM i's

[5] X_i, ϵ_i, and V_i can be scalars, vectors, or matrices. Further, they can be individual-specific, alternative-specific, and pair-specific. Lastly, finiteness of $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ is only needed in Proposition 3 to make the construction of the sharp identified set computationally tractable. However, we assume it since the beginning to simplify the exposition.

[6] Note that the state of the world can vary across agents, as highlighted by subscript i in (x_i, e_i, v_i). Further, if two agents i, j are such that $(x_i, e_i) \neq (x_j, e_j)$, then $P_{\epsilon|X}(\cdot|x_i)$ and $P_{V|X,\epsilon}(\cdot|x_i, e_i)$ can be different from $P_{\epsilon|X}(\cdot|x_j)$ and $P_{V|X,\epsilon}(\cdot|x_j, e_j)$, respectively.

[7] One representation of the complete information structure is $\mathcal{T}_i \equiv \mathcal{V}, P^i_{T|X,\epsilon,V}(v|x, e, v) = 1\ \forall x \in \mathcal{X}, \forall e \in \mathcal{E}$, and $\forall v \in \mathcal{V}$.

[8] One representation of the degenerate information structure is $\mathcal{T}_i \equiv \{t\}, P^i_{T|X,\epsilon,V}(t|x, e, v) = 1\ \forall x \in \mathcal{X}, \forall e \in \mathcal{E}$, and $\forall v \in \mathcal{V}$, where t is any real number. Note that under the degenerate information structure DM i's posterior is equal to DM i's prior about V_i.

"*augmented choice problem*".

Note that information structures can vary across decision makers. This is because different agents could have different attention constraints and, consequently, sustain different costs to gather information on the state of the world. More precisely, even if two agents i, j are such that $(x_i, e_i, v_i) = (x_j, e_j, v_j)$, it may be that $P^i_{T|X,\epsilon,V}(\cdot|x_i, e_i, v_i) \neq P^j_{T|X,\epsilon,V}(\cdot|x_j, e_j, v_j)$ and, hence, $P^i_{V|X,\epsilon,T}(\cdot|x_i, e_i, t_i) \neq P^j_{V|X,\epsilon,T}(\cdot|x_j, e_j, t_j)$. Also, it may be that $t_i = t_j$ but $P^i_{T|X,\epsilon,V}(\cdot|x_i, e_i, v_i) \neq P^j_{T|X,\epsilon,V}(\cdot|x_j, e_j, v_j)$. Such heterogeneity is highlighted by the superscript/subscript i in $\mathcal{P}^i_{T|X,\epsilon,V}$, $\mathcal{P}^i_{V|X,\epsilon,T}$, $\mathcal{T}_i$, and S_i. Lastly, note that conditional signal densities can be arbitrarily correlated with agents' preferences.

We now define an optimal strategy of DM i when facing the augmented choice problem (G, S_i). Let Y_i be a random variable representing DM i's choice. A (mixed[9]) strategy in the augmented choice problem (G, S_i) is a family of probability mass functions of Y_i conditional on every realisation (x, e, t) of (X_i, ϵ_i, T_i), i.e.,

$$\mathcal{P}^i_{Y|X,\epsilon,T} \equiv \{P^i_{Y|X,\epsilon,T}(\cdot|x, e, t) \in \Delta(\mathcal{Y}) : x \in \mathcal{X}, e \in \mathcal{E}, t \in \mathcal{T}_i\}.$$

$\mathcal{P}^i_{Y|X,\epsilon,T}$ is an optimal strategy of the augmented choice problem (G, S_i) if, for each $x \in \mathcal{X}$, $e \in \mathcal{E}$, and $t \in \mathcal{T}_i$, DM i maximises her expected payoff by choosing alternative $y \in \mathcal{Y}$ such that $P^i_{Y|X,\epsilon,T}(y|x, e, t) > 0$.

Definition 1. (*Optimal strategy of the augmented choice problem* (G, S_i)) $\mathcal{P}^i_{Y|X,\epsilon,T}$ is an optimal strategy of the augmented choice problem (G, S_i) if $\forall x \in \mathcal{X}$, $\forall e \in \mathcal{E}$, and $\forall t \in \mathcal{T}_i$,

$$\sum_{v \in \mathcal{V}} u(y, x, e, v) P^i_{T|X,\epsilon,V}(t|x, e, v) P_{V|X,\epsilon}(v|x, e) \geq \sum_{v \in \mathcal{V}} u(\tilde{y}, x, e, v) P^i_{T|X,\epsilon,V}(t|x, e, v) P_{V|X,\epsilon}(v|x, e),$$

$\forall y \in \mathcal{Y}$ such that $P^i_{Y|X,\epsilon,T}(y|x, e, t) > 0$, and $\forall \tilde{y} \in \mathcal{Y} \setminus \{y\}$.[10] $\diamond$

Let $\mathcal{S}$ denote the set of all admissible information structures. By using the continuity of DM i's expected payoff with respect to Y_i (in the discrete metric), it is possible to show that an optimal strategy of the augmented choice problem (G, S_i) exists for every $S_i \in \mathcal{S}$, even though it may not be unique.

Proposition 1. (*Existence of optimal strategy of the augmented choice problem* (G, S_i)) The augmented choice problem (G, S_i) admits an optimal strategy, $\mathcal{P}^i_{Y|X,\epsilon,T}$, for every $S_i \in \mathcal{S}$. $\diamond$

Before concluding, let us remark that various discrete choice models that have been analysed in the literature can be interpreted as augmented choice problems. For instance, in standard

[9] In the presence of ties.

[10] See Appendix A for further notes on Definition 1. We explain how the product $P^i_{T|X,\epsilon,V}(t|x, e, v) P_{V|X,\epsilon}(v|x, e)$ in the inequality of Definition 1 relates to DM i's posterior. We also provide an equivalent definition of an optimal strategy of the augmented choice problem (G, S_i). Finally, we use Definition 1 to formally define DM i's endogenous consideration set.

discrete choice models (e.g., Logit model, Nested Logit model, Mixed Logit model), DM i knows the realisation, v_i, of her tastes, V_i. That is, DM i is endowed with the complete information structure. Discrete choice models with risk aversion typically assume that DM i' belief on a future risky event, V_i, follows some parametric model and can be identified from ex-post data (see, e.g., Barseghyan, Molinari, O'Donoghue, and Teitelbaum, 2018 for a review). In our framework, this can be represented by setting DM i's prior equal to such identified belief and imposing that DM i processes the degenerate information structure. Discrete choice models with rational inattention parameterise the attentional costs sustained by DM i to acquire information about V_i and assume that DM i processes the information structure maximising her expected payoff minus attentional costs (e.g., Caplin and Dean, 2015; Matějka and McKay, 2015). Also some search protocols can be rewritten in terms of information structures (e.g., Hébert and Woodford, 2018; Morris and Strack, 2019). More detailed examples are in Section 4.

3 Identification

In this section we discuss identification of the primitives, u, $\mathcal{P}_{V|X,\epsilon}$, and $\mathcal{P}_{\epsilon|X}$. We assume that the researcher has data on choices made by many i.i.d. DMs facing the decision problem above and, possibly, one some covariates which may or may not include the state of the world. However, the researcher does not observe information structures, which remain latent, potentially heterogenous across agents, and arbitrarily endogenous. We develop a methodology that remains agnostic about information structures. We proceed under the only assumption that every DM i in the population observes (x_i, e_i) and is *at least* aware of the baseline choice problem G.

Let us start by formally illustrating the assumptions on the data generating process (hereafter, DGP). In what follows, superscript 0 distinguishes the *true* value of the primitives from other possible values. The rest of the notation has been introduced in Section 2.

Assumption 1. (*DGP*) The sets $\mathcal{Y}$, $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ are finite and known by the researcher. Nature repeats the following procedure for $i = 1, ..., n$, in a mutually independent manner, with n large:

1. DM i is endowed by nature with a realisation, (x_i, e_i, v_i), of (X_i, ϵ_i, V_i). x_i and e_i are drawn at random from P^0_X and $P^0_{\epsilon|X}(\cdot|x_i)$, respectively. DM i observes (x_i, e_i). DM i does not observe v_i. However, DM i believes that v_i has been drawn at random from $P^0_{V|X,\epsilon}(\cdot|x_i, e_i)$. The researcher observes x_i. Sometimes, the researcher may also observe v_i. $G^0 \equiv (\mathcal{Y}, \mathcal{X}, \mathcal{E}, \mathcal{V}, u^0, \mathcal{P}^0_{V|X,\epsilon}, \mathcal{P}^0_{\epsilon|X})$ constitutes the baseline choice problem.

2. DM i processes some information structure from the set of admissible information structures, $S^0_i \equiv (\mathcal{T}^0_i, \mathcal{P}^{i,0}_{T|X,\epsilon,V}) \in \mathcal{S}$.

3. DM i faces the augmented choice problem (G^0, S_i^0).

4. DM i chooses alternative y_i from $\mathcal{Y}$ according to the notion of optimal strategy of the augmented choice problem (G^0, S_i^0) provided in Definition 1. If needed, DM i adopts some tie-breaking rule. The researcher observes y_i.

$\diamond$

Assumption 1 is similar to what is discussed in Magnolfi and Roncoroni (2017) and Syrgkanis, Tamer, and Ziani (2018) for an entry game setting and an auction setting, respectively. It summarises the model of Section 2 and draws attention to the fact that the researcher is not aware of agents' information structures and tie-breaking rules, which can be endogenous and heterogenous.

The probability mass function of (Y_i, X_i) which results from the decision problem is denoted by $P^0_{Y,X} \in \Delta(\mathcal{X} \times \mathcal{Y})$. $P^0_{Y,X}$ is nonparametrically identified by the sampling process and, hence, treated as known in the identification analysis.

In some settings, v_i is observed by the researcher, together with (x_i, y_i) for $i = 1, ..., n$. For example, in discrete choice models of insurance plans, the researcher typically observes the ex-post claim experience of the agents in the sample. In those cases, $\mathcal{P}^0_{V|X,\epsilon}$ could be identified directly from such additional data (under further assumptions). More details are in Section 4. In our general discussion below, for simplicity we treat v_i as unobserved by the researcher for $i = 1, ..., n$.

The sets $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ are assumed finite in order to make the construction of the sharp identified set computationally tractable. When this is not the case, one can discretise them, as is common in the empirical literature with partially identified parameters.

The fact that the sets $\mathcal{Y}$, $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ are finite implies that the image sets of u^0, $\mathcal{P}^0_{V|X,\epsilon}$, and $\mathcal{P}^0_{\epsilon|X}$ are finite. Hence, assuming that the sets $\mathcal{Y}$, $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ are finite corresponds to *parameterising* u^0, $\mathcal{P}^0_{V|X,\epsilon}$, and $\mathcal{P}^0_{\epsilon|X}$. In particular, u^0 is fully characterised by $|\mathcal{Y}| \cdot |\mathcal{X}| \cdot |\mathcal{E}| \cdot |\mathcal{V}|$ image points. Similarly, $P^0_{\epsilon|X}(\cdot|x)$ is fully characterised by $|\mathcal{E}|$ image points for each $x \in \mathcal{X}$ and $P^0_{V|X,\epsilon}(\cdot|x, e)$ is fully characterised by $|\mathcal{V}|$ image points for each $(x, e) \in \mathcal{X} \times \mathcal{E}$. We denote by $\theta^0 \in \Theta \subset \mathbb{R}^K$ the vector collecting *all such image points*, with length $K \equiv |\mathcal{Y}| \cdot |\mathcal{X}| \cdot |\mathcal{E}| \cdot |\mathcal{V}| + |\mathcal{E}| \cdot |\mathcal{X}| + |\mathcal{V}| \cdot |\mathcal{E}| \cdot |\mathcal{X}|$. θ^0 is the vector of primitives that we want to identify. If the elements of the sets $\mathcal{Y}$, $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ are vectors or matrices with large dimensions, then K is large too. In this case, to reduce the computational burden of the procedure, one may want to parameterise further u^0, $\mathcal{P}^0_{V|X,\epsilon}$, and $\mathcal{P}^0_{\epsilon|X}$, by assuming that u^0 is governed by the vector of parameters θ^0_1, $\mathcal{P}^0_{\epsilon|X}$ belongs to parametric family of probability distributions indexed by θ^0_2, and $\mathcal{P}^0_{V|X,\epsilon}$ belongs to parametric family of probability distributions indexed by θ^0_3. This is what we do in our simulations and empirical application. We continue the analysis without considering such additional parameterisation.

Note that Assumption 1 allows for arbitrary correlation between X_i and (ϵ_i, V_i). This is not surprising. In fact, assuming that the sets $\mathcal{X}$, $\mathcal{E}$, and $\mathcal{V}$ are finite corresponds to parameterising any correlation between X_i and (ϵ_i, V_i).

Before proceeding, let us introduce some useful notation. In what follows, we denote by $\mathcal{P}^0_{Y|X}$ the family of probability mass functions of Y_i conditional on every realisation x of X_i induced by $P^0_{Y,X}$. For each $x \in \mathcal{X}$ and $P_{Y|X}(\cdot|x) \in \Delta(\mathcal{Y})$, let us rearrange the one-to-one image set of the mapping $y \in \mathcal{Y} \mapsto P_{Y|X}(\cdot|x) \in \Delta(\mathcal{Y})$ into a $|\mathcal{Y}| \times 1$ dimensional vector. With some abuse of notation, let us still denote such a vector by $P_{Y|X}(\cdot|x)$. For each $x \in \mathcal{X}$ and $P_{\epsilon|X}(\cdot|x) \in \Delta(\mathcal{E})$, let us rearrange the one-to-one image set of the mapping $e \in \mathcal{E} \mapsto P_{\epsilon|X}(\cdot|x) \in \Delta(\mathcal{E})$ into a $|\mathcal{E}| \times 1$ dimensional vector. With some abuse of notation, let us still denote such a vector by $P_{\epsilon|X}(\cdot|x)$. Further, let us still denote the collection of these vectors across all $x \in \mathcal{X}$ by $\mathcal{P}_{\epsilon|X}$. Similarly, for each $(x, e) \in \mathcal{X} \times \mathcal{E}$ and $P_{V|X,\epsilon}(\cdot|x, e) \in \Delta(\mathcal{V})$, let us rearrange the one-to-one image set of the mapping $v \in \mathcal{V} \mapsto P_{V|X,\epsilon}(\cdot|x, e) \in \Delta(\mathcal{V})$ into a $|\mathcal{V}| \times 1$ dimensional vector. With some abuse of notation, let us still denote such a vector by $P_{V|X,\epsilon}(\cdot|x, e)$. Further, let us still denote the collection of these vectors across all $(x, e) \in \mathcal{X} \times \mathcal{E}$ by $\mathcal{P}_{V|X,\epsilon}$. Lastly, let us rearrange the one-to-one image set of the mapping $(y, x, e, v) \in \mathcal{Y} \times \mathcal{X} \times \mathcal{E} \times \mathcal{V} \mapsto u(y, x, e, v)$ into a $|\mathcal{Y}| \cdot |\mathcal{X}| \cdot |\mathcal{E}| \cdot |\mathcal{V}| \times 1$ dimensional vector. With some abuse of notation, let us still denote such a vector by u. $\theta \equiv (u, \mathcal{P}_{\epsilon|X}, \mathcal{P}_{V|X,\epsilon})$ of length K represents a generic element of Θ. $S \equiv (\mathcal{T}, \mathcal{P}_{T|X,\epsilon,V})$ represents a generic element of $\mathcal{S}$. Given $\theta \in \Theta$, we denote by $G^\theta \equiv (\mathcal{Y}, \mathcal{X}, \mathcal{E}, \mathcal{V}, u, \mathcal{P}_{V|X,\epsilon}, \mathcal{P}_{\epsilon|X})$ the corresponding baseline choice problem.

Given the absence of restrictions on information structures and tie-breaking rules, the model is incomplete in the sense of Tamer (2003). This raises the possibility of partial identification of θ^0 and, consequently, the challenge of tractably characterising the set of θs exhausting all the implications of the model and data, i.e., the sharp identified set for θ^0.

Intuitively, the sharp identified set for θ^0 is the set of θs for which the model predicts a probability mass function of (Y_i, X_i) that matches with $P^0_{Y,X}$. More formally, for each $\theta \in \Theta$ and $S \in \mathcal{S}$, let $\mathcal{R}^{\theta,S}$ be the collection of optimal strategies of the augmented choice problem (G^θ, S). Lastly, for each $\theta \in \Theta$ and $x \in \mathcal{X}$, let $\bar{\mathcal{R}}^\theta_{Y|x}$ be the collection of probability mass functions of Y_i conditional on $X_i = x$ that are induced by the model's optimal strategies under θ, while remaining agnostic about information structures. That is,

$$\bar{\mathcal{R}}^\theta_{Y|x} \equiv \text{Conv}\Big\{ P_{Y|X}(\cdot|x) \in \Delta(\mathcal{Y}) : P_{Y|X}(y|x) = \int_{\mathcal{T}\times\mathcal{V}\times\mathcal{E}} P_{Y|X,\epsilon,T}(y|x,e,t) P_{T|X,\epsilon,V}(t|x,e,v) P_{V|X,\epsilon}(v|x,e) P_{\epsilon|X}(e|x) d(t,v,e) \; \forall y \in \mathcal{Y}, \; \mathcal{P}_{Y|X,\epsilon,T} \in \mathcal{R}^{\theta,S}, S \in \mathcal{S} \Big\}, \tag{1}$$

where we have used the fact that Y_i is independent of V_i conditional on (X_i, ϵ_i, T_i), because DM i's information about V_i is fully captured by T_i. Convexification (via the convex hull operator, $\text{Conv}\{\cdot\}$) allows us to include in $\bar{\mathcal{R}}^\theta_{Y|x}$ probability mass functions of Y_i conditional on $X_i = x$ that are mixtures across information structures and tie-breaking rules. Importantly, this implies that information structures and tie-breaking rules can vary across agents in our population. It follows that the sharp identified set for θ^0 can be defined as

$$\Theta^* \equiv \{\theta \in \Theta : P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{R}}^{\theta}_{Y|x} \ \forall x \in \mathcal{X}\}. \tag{2}$$

Unfortunately, the definition of Θ^* in (2) seems hardly useful in practice. This is because computing $\bar{\mathcal{R}}^{\theta}_{Y|x}$ is intractable due to the necessity of exploring the large class $\mathcal{S}$. In what follows, we explain how to overcome such an issue by exploiting Theorem 1 in Bergemann and Morris (2016). The theorem characterises DM i's optimal behaviour in a way that is valid for, and in this sense robust to, all possible information structures DM i may process. In other words, the theorem finds a map from the model's primitives to DM i's optimal behaviour that does not depend on the specification of DM i's information structure. Therefore, Θ^* can be rewritten by using the inverse of such a map.

More precisely, we first introduce the notion of Bayesian Persuasion or one-player Bayes Correlated Equilibrium (hereafter, 1BCE) provided in Kamenica and Gentzkow (2011) and Bergemann and Morris (2013; 2016), respectively.[11]

Definition 2. (*1BCE of the baseline choice problem G^θ*) Fix $\theta \equiv (u, \mathcal{P}_{\epsilon|X}, \mathcal{P}_{V|X,\epsilon}) \in \Theta$. A family of probability mass functions of (Y_i, V_i) conditional on every realisation (x, e) of (X_i, ϵ_i),

$$\mathcal{P}_{Y,V|X,\epsilon} \equiv \{P_{Y,V|X,\epsilon}(\cdot|x,e) \in \Delta(\mathcal{Y} \times \mathcal{V}) : x \in \mathcal{X}, e \in \mathcal{E}\},$$

is a 1BCE of the baseline choice problem G^θ if:

1. It is *consistent* with the baseline choice problem G^θ, i.e., when integrating $P_{Y,V|X,\epsilon}(\cdot|x,e)$ with respect to Y_i, one obtains the prior, $P_{V|X,\epsilon}(\cdot|x,e)$, $\forall x \in \mathcal{X}$ and $\forall e \in \mathcal{E}$. That is,

$$\sum_{y \in \mathcal{Y}} P_{Y,V|X,\epsilon}(y, v|x, e) = P_{V|X,\epsilon}(v|x,e) \ \forall x \in \mathcal{X}, \forall e \in \mathcal{E}, \forall v \in \mathcal{V}.$$[12]

2. It is *obedient*, i.e., an agent who is recommended alternative $y \in \mathcal{Y}$ by an omniscient mediator has no incentive to deviate. That is,

$$\sum_{v \in \mathcal{V}} u(y, x, e, v) P_{Y,V|X,\epsilon}(y, v|x, e) \geq \sum_{v \in \mathcal{V}} u(\tilde{y}, x, e, v) P_{Y,V|X,\epsilon}(y, v|x, e),$$
$$\forall y \in \mathcal{Y}, \forall \tilde{y} \in \mathcal{Y} \setminus \{y\}, \forall x \in \mathcal{X}, \forall e \in \mathcal{E}.$$

◇

We now illustrate the fundamental result our methodology relies on, i.e., Theorem 1 in Bergemann and Morris (2016). The theorem shows that, for any given $\theta \in \Theta$, the collection

[11] The notions of Bayesian Persuasion and 1BCE coincide. Specifically, Kamenica and Gentzkow (2011) consider a framework where a sender chooses an information structure, $S_i \in \mathcal{S}$, to give to receiver i and then receiver i chooses an alternative. Instead of letting the sender choose an $S_i \in \mathcal{S}$, Bergemann and Morris (2019) finds that this is equivalent to letting the sender choose her favourite 1BCE.

[12] Note that consistency requires that DM i applies the Bayes rule correctly to update her prior.

of probability mass functions of (Y_i, V_i) conditional on (X_i, ϵ_i) that are predicted by the model above if DM i were to process *some* information structure, $S_i \in \mathcal{S}$, is equal to the collection of 1BCE of the baseline choice problem G^θ.[13] That is, it is equivalent to the collection of probability mass functions of (Y_i, V_i) conditional on (X_i, ϵ_i) in a mediated decision problem where the mediator directly provides recommendations to DM i and these recommendations are incentive compatible.

Theorem 1. (*Bergemann and Morris, 2016*) Fix $\theta \equiv (u, \mathcal{P}_{\epsilon|X}, \mathcal{P}_{V|X,\epsilon}) \in \Theta$. $\mathcal{P}_{Y,V|X,\epsilon}$ is a 1BCE of the baseline choice problem G^θ if and only if there exists an information structure, $S \equiv (\mathcal{T}, \mathcal{P}_{T|X,\epsilon,V}) \in \mathcal{S}$, and an optimal strategy, $\mathcal{P}_{Y|X,\epsilon,T}$, of the augmented choice problem (G^θ, S), such that $\mathcal{P}_{Y,V|X,\epsilon}$ is induced by $\mathcal{P}_{Y|X,\epsilon,T}$.[14] ◇

Note that Theorem 1 also implies that a 1BCE of the baseline choice problem G^θ exists for each $\theta \in \Theta$. Indeed, fix any information structure $S \in \mathcal{S}$. Let $\mathcal{P}_{Y|X,\epsilon,T}$ be an optimal strategy of the augmented choice problem (G^θ, S), which exists by Proposition 1. Let $\mathcal{P}_{Y,V|X,\epsilon}$ be the family of probability mass functions of (Y_i, V_i) conditional on every realisation (x, e) of (X_i, ϵ_i) induced by $\mathcal{P}_{Y|X,\epsilon,T}$. Then, by Theorem 1, $\mathcal{P}_{Y,V|X,\epsilon}$ is a 1BCE of the baseline choice problem G^θ. Therefore, the set of 1BCE of the baseline choice problem G^θ is non-empty. Furthermore, the set of 1BCE of the baseline choice problem G^θ is typically non-singleton. Indeed, if the set of 1BCE was a singleton, then information would be essentially irrelevant, i.e., a certain alternative would be optimal regardless of any extra information that agents might process.

We now exploit Theorem 1 to represent Θ^* in an equivalent but more tractable way. For each $\theta \in \Theta$, let $\mathcal{Q}^\theta$ be the collection of 1BCEs of the baseline choice problem G^θ. Moreover, for each $\theta \in \Theta$ and $x \in \mathcal{X}$, let $\bar{\mathcal{Q}}^\theta_{Y|x}$ be the collection of probability mass functions of Y_i conditional on $X_i = x$ that are induced by the 1BCEs of the baseline choice problem G^θ. That is,

$$\begin{aligned}\bar{\mathcal{Q}}^\theta_{Y|x} \equiv \Big\{ & P_{Y|X}(\cdot|x) \in \Delta(\mathcal{Y}) : \\ & P_{Y|X}(y|x) = \sum_{(e,v)\in\mathcal{E}\times\mathcal{V}} P_{Y,V|X,\epsilon}(y, v|x, e) P_{\epsilon|X}(e|x) \ \forall y \in \mathcal{Y}, \mathcal{P}_{Y,V|X,\epsilon} \in \mathcal{Q}^\theta \Big\}.\end{aligned} \tag{3}$$

Note that $\bar{\mathcal{Q}}^\theta_{Y|x}$ is convex and, hence, we do not need to take the convex hull of $\bar{\mathcal{Q}}^\theta_{Y|x}$ to allow for heterogeneity of information structures and tie-breaking rules. In fact, for each $x \in \mathcal{X}$ and $e \in \mathcal{E}$, $\mathcal{Q}^\theta$ is convex because it is characterised by equalities and inequalities that are linear in $P_{Y,V|X,\epsilon}(\cdot|x, e)$, as can be seen from Definition 2. Therefore, for each $x \in \mathcal{X}$ and $\theta \in \Theta$, $\bar{\mathcal{Q}}^\theta_{Y|x}$ is

[13] Recall that Theorem 1 in Bergemann and Morris (2016) is valid for a general n-player game, where $n \geq 1$. It is used here for a one-player game. Note that, in a one-player game, the notion of Bayes Correlated Equilibrium does not refer to agents best responding to each other. Instead, it refers to the optimal behaviour of a single agent in a decision problem.

[14] Suppose $\mathcal{T}$ is finite. Then, by "induced" we mean

$$P_{Y,V|X,\epsilon}(y, v|x, e) = \sum_{t\in\mathcal{T}} P_{Y|X,\epsilon,T}(y|x, e, t) P_{T|X,\epsilon,V}(t|x, e, v) P_{V|X,\epsilon}(v|x, e),$$

$\forall y \in \mathcal{Y}$, $\forall v \in \mathcal{V}$, $\forall x \in \mathcal{X}$, and $\forall e \in \mathcal{E}$.

also convex. Theorem 1 implies that $\bar{\mathcal{R}}^{\theta}_{Y|x} = \bar{\mathcal{Q}}^{\theta}_{Y|x}$ $\forall x \in \mathcal{X}$ and $\forall \theta \in \Theta$. Thus, one can rewrite Θ^* by using the notion of 1BCE, as formalised in Proposition 2.

Proposition 2. (*Characterisation of* Θ^* *through the notion of 1BCE*) Let

$$\Theta^{**} \equiv \{\theta \in \Theta : P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x} \ \forall x \in \mathcal{X}\}.$$

Under Assumption 1, $\Theta^* = \Theta^{**}$. ◇

Constructing Θ^* as characterised in Proposition 2 is computationally tractable by leveraging on the convexity of $\bar{\mathcal{Q}}^{\theta}_{Y|x}$ for each $x \in \mathcal{X}$ and $\theta \in \Theta$. This is formalised in Proposition 3. Before presenting Proposition 3, let us introduce some useful notation. For each $(x, e) \in \mathcal{X} \times \mathcal{E}$ and $P_{Y,V|X,\epsilon}(\cdot|x, e) \in \Delta(\mathcal{Y} \times \mathcal{V})$, let us rearrange the one-to-one image set of the mapping $(y, v) \in \mathcal{Y} \times \mathcal{V} \mapsto P_{Y,V|X,\epsilon}(\cdot|x, e) \in \Delta(\mathcal{Y} \times \mathcal{V})$ into a $|\mathcal{Y}| \cdot |\mathcal{V}| \times 1$ dimensional vector. With some abuse of notation, let us still denote such a vector by $P_{Y,V|X,\epsilon}(\cdot|x, e)$. Further, let us still denote the collection of these vectors across all $(x, e) \in \mathcal{X} \times \mathcal{E}$ by $\mathcal{P}_{Y,V|X,\epsilon}$.

Proposition 3. (*Construction of* Θ^*) Fix $\theta \equiv (u, \mathcal{P}_{\epsilon|X}, \mathcal{P}_{V|X,\epsilon}) \in \Theta$. Under Assumption 1, $\theta \in \Theta^*$ if and only if the following linear programming problem has a solution with respect to $\mathcal{P}_{Y,V|X,\epsilon}$:

$$\text{[1BCE-Consistency]:} \quad \sum_{y \in \mathcal{Y}} P_{Y,V|X,\epsilon}(y, v|x, e) = P_{V|\epsilon,X}(v|e, x) \ \forall v \in \mathcal{V}, \forall e \in \mathcal{E}, \forall x \in \mathcal{X},$$

$$\text{[1BCE-Obedience]:} \quad -\sum_{v \in \mathcal{V}} P_{Y,V|X,\epsilon}(y, v|x, e)[u(y, x, e, v) - u(y', x, e, v)] \leq 0 \ \forall y \in \mathcal{Y}, \forall y' \in \mathcal{Y} \setminus \{y\}, \forall e \in \mathcal{E}, \forall x \in \mathcal{X},$$

$$\text{[1BCE-Model predictions]:} \quad P^0_{Y|X}(y|x) = \sum_{(e,v) \in \mathcal{E} \times \mathcal{V}} P_{Y,V|X,\epsilon}(y, v|x, e) P_{\epsilon|X}(e|x) \ \forall y \in \mathcal{Y}, \forall x \in \mathcal{X}.$$

◇

Note that the linear programming problem of Proposition 3 can incorporate various classes of nonparametric assumptions into $\mathcal{P}_{V|X,\epsilon}$ and $\mathcal{P}_{\epsilon|X}$, such as independence of (ϵ_i, V_i) from X_i, symmetry of marginals around zero, identical marginals, quantile restrictions, etc. These assumptions are simply added as linear constraints.

4 Examples and simulations

As a first example, we consider the Nested Logit model with one nest collecting all goods but the outside option. In particular, following our general notation, we set

$$u(y, X_i, \epsilon_i, V_i) = \begin{cases} \beta' X_{iy} + \lambda \log(\epsilon_i) + \lambda V_{iy} & \text{if } y \in \mathcal{Y} \setminus \{0\}, \\ V_{i0} & \text{if } y = 0, \end{cases} \tag{4}$$

where $0 \in \mathcal{Y}$ is the outside option, $\mathcal{Y}$ has cardinality $L+1$, $X_i \equiv (X_{i,1}, ..., X_{i,L})$ is an $M \times L$ matrix of inside goods' covariates, ϵ_i and $V_i \equiv (V_{i,0}, ..., V_{i,L})$ represent DM i's tastes, and $\lambda \in (0,1)$. $\{\epsilon_i, V_{i,0}, ..., V_{i,L}\}$ are mutually independent and independent of X_i. The densities of ϵ_i and V_{iy} are parameterised as in Cardell (1997), so that $\eta_{iy} \equiv \lambda \log(\epsilon_i) + \lambda V_{iy}$ has a standard Gumbel density and the CDF of $(\eta_{i1}, ..., \eta_{iL})$ evaluated at $(s_1, ..., s_L)$ is $\exp(-(\sum_{y=1}^{L} \exp(-s_y/\lambda))^{\lambda})$ as prescribed by the Nested Logit model.[15]

In the standard Nested Logit model, every agent is assumed to know the realisation of all the payoff-relevant variables before choosing. Here, instead, DM i may be uncertain about the realisation of V_i. For example, if $\mathcal{Y}$ collects transportation modes (where the outside option is not travelling), V_i could represent DM i's taste for the pro-environemnt features of the various transportation modes. DM i has a prior about V_i, which we assume to obey the Nested Logit parameterisation above. Further, DM i may process additional information to refine her prior by, for instance, investigating the technical characteristics of each transportation mode, seeking out reviews, etc. We formalise such additional information through the notion of information structure. The researcher remains ignorant about DM i's information structure. DM i's information structure could be arbitrarily correlated with (X_i, ϵ_i, V_i). Also, different agents may process different information structures. Our methodology permits to study identification of (β, λ) while leaving information structure unspecified and potentially heterogeneous across agents.

We start by constructing the collection of choice probabilities predicted by 1BCEs for a given value of covariates and parameters. This step serves to get a preliminary understanding about the identifying power of 1BCE. In particular, we want to exclude the possibility that 1BCE rationalises every probability distribution in the unit simplex, because this would imply that 1BCE has no identifying power. We set $L = 2$, $\beta = 0$, and $\lambda = 0.5$. Further, we discretise the densities of ϵ_i and V_i to have supports $\mathcal{E} \equiv \{0.1, 1, 2, ..., 50\}$ and $\mathcal{V} \equiv \{-2, -1, ..., 6\}^3$, respectively.[16] Hereafter, we refer to this DGP as DGP1. Let $\bar{\mathcal{R}}_Y^{\beta,\lambda,\text{comp}}$ be the collection of choice probabilities induced by the model's optimal strategies when the researcher assumes that agents are endowed with the complete information structure. Let $\bar{\mathcal{R}}_Y^{\beta,\lambda,\text{deg}}$ be the collection of choice probabilities that are induced by the model's optimal strategies when the researcher assumes that agents are endowed with the degenerate information structure. Finally, recall that $\bar{\mathcal{Q}}_Y^{\beta,\lambda}$ is the collection of choice probabilities that are induced by 1BCEs, as defined in Equation (3). Figure 1 represents $\bar{\mathcal{Q}}_Y^{\beta,\lambda}$ (black region), $\bar{\mathcal{R}}_Y^{\beta,\lambda,\text{comp}}$ (red region), and $\bar{\mathcal{R}}_Y^{\beta,\lambda,\text{deg}}$ (blue region). By Theorem 1, $\bar{\mathcal{R}}_Y^{\beta,\lambda,\text{comp}}$ and $\bar{\mathcal{R}}_Y^{\beta,\lambda,\text{comp}}$ are subsets of $\bar{\mathcal{Q}}_Y^{\beta,\lambda}$. Further, note that $\bar{\mathcal{Q}}_Y^{\beta,\lambda}$ is a strict and relatively small subset of the unit simplex, which reassures us about the identifying power

[15] See also Galichon (2019) regarding the random utility representation of the Nested Logit model.

[16] To discretise a density, we first discretise its support and then transform the density into a probability mass function. For example, $P_\epsilon(e) = \frac{f_\epsilon(e)}{\sum_{e \in \mathcal{E}} f_\epsilon(e)}$ $\forall e \in \mathcal{E}$, where f_ϵ is ϵ_i's original density. The support should be discretised in a way such that the resulting probability mass function preserves the shape of the original density. For a list of methods to discretise densities see Bracquemond and Gaudoin (2003), Lai (2013), and Chakraborty (2015).

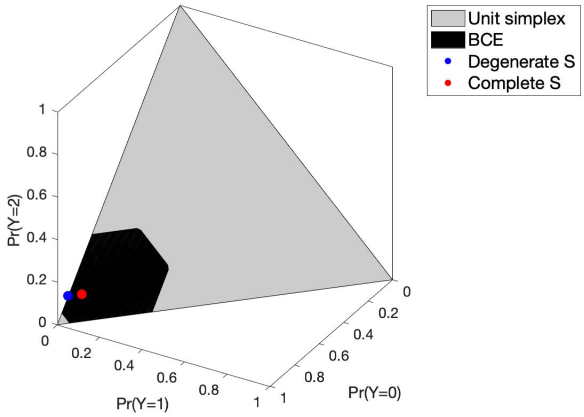

Figure 1: The figure represents $\bar{\mathcal{Q}}_Y^{\beta,\lambda}$ (black region), $\bar{\mathcal{R}}_Y^{\beta,\lambda,\mathrm{comp}}$ (red region), and $\bar{\mathcal{R}}_Y^{\beta,\lambda,\mathrm{deg}}$ (blue point) under DGP1.

of 1BCE in this context.

We now move to simulate data from (4) and construct the sharp identified set for the parameters of interest as outlined by Proposition 3. We consider a DGP slightly more complicated than DGP1. In particular, to generate the data, we set $L = 3$, $M = 1$, $\beta = 1.6$, and $\lambda = 0.5$. The probability mass function of X_i, P_X, is obtained as the density of a normal random vector with mean and variance covariance matrix

$$\mu_X \equiv (0.629, 0.812, -0.746)', \; \Sigma_X \equiv \begin{pmatrix} 3.913 & 0.455 & 0.531 \\ 0.455 & 3.547 & 0.558 \\ 0.531 & 0.558 & 3.971 \end{pmatrix},$$

respectively, discretised to have support $\mathcal{X} \equiv \{-1, 0, 1\}^3$. We discretise the densities of ϵ_i and V_i to have supports $\mathcal{E} \equiv \{0.1, 1, 2, ..., 50\}$ and $\mathcal{V} \equiv \{-2, -1, ..., 6\}^3$, respectively. In the presence of ties, agents select one of the indifferent alternatives uniformly at random. Finally, the empirical choice probabilities are derived under the assumption that half of the population is endowed with the complete information structure (i.e., half of the population processes enough information to discover the exact realisation of V_i) and half of the population is endowed with the degenerate information structure (i.e., half of the population does not process additional information and has a posterior equal to the prior). Hereafter, we refer to this DGP as DGP2. The black region in Figure 2 represents the sharp identified set. The red dot in Figure 2 represents the true value of the parameters. The black region is tight and informative about the signs and magnitudes of the parameters.

As a second example, we consider a discrete choice model of insurance plans. Specifically, DM i faces an underlying risk of a loss and can choose among L insurance plans. The loss event is denoted by V_i. $V_i = 1$ if the loss event occurs, and 0 otherwise. The loss event occurs with probability μ_i. Each insurance plan $y \in \mathcal{Y} \equiv \{1, ..., L\}$ is characterised by a deductible, D_y, and a premium, P_{iy}. Further, DM i is endowed with some wealth (Wealth_i) and a vector of

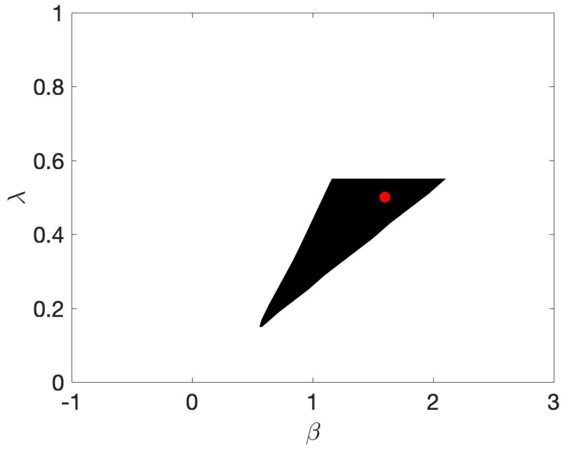

Figure 2: The figure is based on DGP2. The black region represents the sharp identified set. The red dot represents the true value of the parameters.

demographic discrete characteristics, Z_i, such as gender, age, insurance score, etc. Following our general notation, we collect $(P_{i,y}, D_y)$ for each insurance plan $y \in \mathcal{Y}$, Wealth$_i$, and Z_i in the vector X_i. The payoff function, u, belongs to the CARA family, i.e., for each $y \in \mathcal{Y}$,

$$u(y, X_i, \epsilon_i, V_i) \equiv \begin{cases} \frac{1-\exp[-\epsilon_i \times (\text{Wealth}_i - P_{i,y} - D_y)]}{\epsilon_i} & \text{if } V_i = 1, \epsilon_i \neq 0, \\ \frac{1-\exp[-\epsilon_i \times (\text{Wealth}_i - P_{i,y})]}{\epsilon_i} & \text{if } V_i = 0, \epsilon_i \neq 0, \\ W_i - P_{i,y} - D_y & \text{if } V_i = 1, \epsilon_i = 0, \\ W_i - P_{i,y} & \text{if } V_i = 0, \epsilon_i = 0, \end{cases} \tag{5}$$

where ϵ_i is the coefficient of absolute risk aversion. Before choosing, DM i is aware of the realisation of (X_i, ϵ_i) but does not observe the realisation of V_i because V_i is realised after the choice has been made. However, DM i has some belief, Ω_i, about V_i taking value 1. DM i chooses insurance plan $y_i \in \mathcal{Y}$ that maximises her expected payoff. That is,

$$y_i \in \text{argmax}_{y \in \mathcal{Y}} \ \Omega_i u(y, X_i, \epsilon_i, 1) + (1 - \Omega_i) u(y, X_i, \epsilon_i, 0).$$

Seminal papers in the literature have studied identification of agents' risk aversion and beliefs in the framework above under various assumption (Barseghyan, Molinari, O' Donoghue, and Teitelbaum, 2013a; 2013b; Barseghyan, Molinari, and Teitelbaum; 2016). A typical restriction consists of: first, imposing that μ_i obeys some parametric model that can be identified from ex-post data on claims; second, imposing that Ω_i is a parametric function of μ_i or that $\Omega_i \equiv \mu_i$. Our methodology allows to investigate identification of agents' risk aversion under weaker restrictions on Ω_i. More precisely, let us interpret μ_i as DM i's prior and Ω_i as DM i's posterior. DM i forms Ω_i by processing some latent and potentially endogenous information structure which may consist, e.g., of checking the technical features of her car, road and traffic conditions, etc. Our methodology allows to conduct identification on μ_i and the distribution

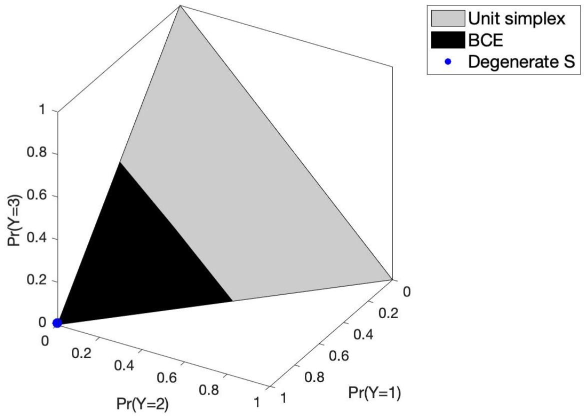

Figure 3: The figure represents $\bar{\mathcal{Q}}_Y^{\beta,\lambda}$ (black region) and $\bar{\mathcal{R}}_Y^{\beta,\lambda,\deg}$ (blue point) under DGP3.

of ϵ_i while allowing Ω_i to be *any Bayes-plausible* posterior.

We start by constructing the collection of choice probabilities predicted by 1BCEs for a given value of covariates and parameters. As earlier, this step serves to get a preliminary understanding about the identifying power of 1BCE. In particular, we set $L = 3$ and $(D_1, D_2, D_3) = (100, 200, 500)$. For each insurance plan $y \in \mathcal{Y}$, $P_{i,y}$ is assumed equal to $P^{\text{base}} \times \lambda_y$, where $(\lambda_1, \lambda_2, \lambda_3) \equiv (5/6, 7/10, 3/10)$ and $P^{\text{base}} = 100$. Given that the payoff function belongs to the CARA family, payoffs can be computed without observing Wealth_i. Z_i is ignored for simplicity. ϵ_i is distributed as a Beta with parameters $\gamma_1 = 1, \gamma_2 = 10$ and support $[0, 0.02]$. Further, for computational tractability, this support is discretised into 21 equidistant points. DM i's prior about $V_i = 1$ (μ_i) is imposed equal to $1 - \Phi(0)$, where Φ is the normal CDF with mean 0 and variance 2. Hereafter, we refer to this DGP as DGP3. As before, let $\bar{\mathcal{R}}_Y^{\gamma_1,\gamma_2,\deg}$ be the collection of choice probabilities induced by the model's optimal strategies under degenerate information structure, and $\bar{\mathcal{Q}}_Y^{\gamma_1,\gamma_2}$ is the collection of choice probabilities that are induced by 1BCEs. Figure 3 represents $\bar{\mathcal{Q}}_Y^{\gamma_1,\gamma_2}$ (black region) and $\bar{\mathcal{R}}_Y^{\gamma_1,\gamma_2,\deg}$ (blue region). As earlier, $\bar{\mathcal{R}}_Y^{\gamma_1,\gamma_2,\deg}$ is a subset of $\bar{\mathcal{Q}}_Y^{\gamma_1,\gamma_2}$. Further, note that $\bar{\mathcal{Q}}_Y^{\gamma_1,\gamma_2}$ is a strict and relatively small subset of the unit simplex, which reassures us about the identifying power of 1BCE in this context.

We now move to simulate data from (5) and construct the sharp identified set for the parameters of interest as outlined by Proposition 3. We consider a DGP slightly more complicated than DGP3. In particular, to generate the data, we set $L = 4$, $(D_1, D_2, D_3, D_4) = (100, 200, 500, 1000)$. For each insurance plan $y \in \mathcal{Y}$, $P_{i,y}$ is assumed equal to $P_i^{\text{base}} \times \lambda_y$, where $(\lambda_1, \lambda_2, \lambda_3, \lambda_4) \equiv (5/6, 7/10, 3/10, 1/10)$ and P_i^{base} is uniformly distributed on $\{100, 200, 300\}$. Z_i is scalar and uniformly distributed on $\{-4, -3.5, -3, ..., 4\}$. ϵ_i is distributed independently of Z_i as a Beta with parameters $\gamma_1 = 1, \gamma_2 = 10$ and support $[0, 0.02]$. Further, for computational tractability, this support is discretised into 21 equidistant points. In the presence of ties, agents select one of the indifferent alternatives uniformly at random. DM i's prior about

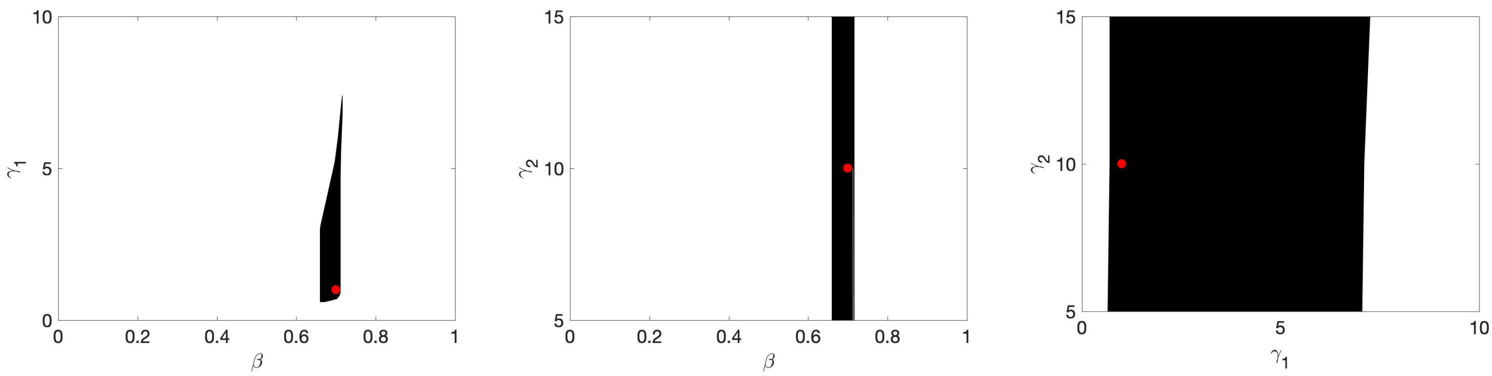

Figure 4: The figure is based on DGP4. The black regions represent the projections of the sharp identified set along each axis. The red dot represents the true value of the parameters.

V_i being equal 1 (μ_i) is assumed to depend on Z_i only and imposed equal to $\Phi(Z_i'\beta)$, where Φ is the normal CDF with mean 0 and variance 2 and $\beta = 0.7$. Finally, the empirical choice probabilities are derived under the assumption that the entire population processes the degenerate information structure. Hereafter, we refer to this DGP as DGP4. The black regions in Figure 4 represent the projections sharp identified set along each dimension. The red dots in Figure 4 represent the true values of the parameters. The projection for β is extremely tight. The projection for γ_1 is less tight but still bounded. The projection for γ_2 is unbounded. Note that if ex-post data on claims are available, then β can be identified directly from those.

5 Inference

Identification of the true parameter vector, θ_0, relies on the assumption that the true probability mass function of the observables, $P^0_{Y,X}$, is known by the researcher. However, when doing an empirical analysis, the researcher should replace $P^0_{Y,X}$ with its sample analogue resulting from having i.i.d. observations, $\{Y_i, X_i\}_{i=1}^n$, and take into account sampling variation. Given $\alpha \in (0,1)$, this section illustrates how to construct a uniformly asymptotically valid $(1-\alpha)$ confidence region, $C_{n,1-\alpha}$, for each $\theta \in \Theta^*$. In particular, we suggest to apply the generalised moment selection procedure by Andrews and Shi (2013) (hereafter, AS), as detailed in Appendix B.1 of Beresteanu, Molchanov, and Molinari (2011) (hereafter, BMM).[17] $C_{n,1-\alpha}$ is obtained by inverting a test with null hypothesis $\text{H}_0 : \theta_0 = \theta$ for every $\theta \in \Theta$. Such a test rejects H_0 if $\text{TS}_n > \hat{c}_{n,1-\alpha}(\theta)$, where TS_n is a test statistic and $\hat{c}_{n,1-\alpha}(\theta)$ is a corresponding critical value. Thus, $C_{n,1-\alpha} \equiv \{\theta \in \Theta\colon \text{TS}_n(\theta) \leq \hat{c}_{n,1-\alpha}(\theta)\}$. The remainder of the section explains how to compute $\text{TS}_n(\theta)$ and $\hat{c}_{n,1-\alpha}(\theta)$ for any $\theta \in \Theta$. Let us anticipate that the computational advantages of using 1BCE are preserved when doing inference.

[17]Note that the characterisation of Θ^* in Proposition 2 is equivalent to the characterisation in Theorem 2.1 of BMM. This is because the Aumann expectation of the random closed set of 1BCE alternative predictions is equal to $\bar{\mathcal{Q}}^{\theta}_{Y|x}$, for each $\theta \in \Theta$ and $x \in \mathcal{X}$.

First, we rewrite the linear programming of Proposition 3 as a collection of conditional moment inequalities. Let us label the elements of $\mathcal{Y}$ as $y^1, ..., y^{|\mathcal{Y}|-1}, y^{|\mathcal{Y}|}$.

Proposition 4. (*Conditional moment inequalities*) Under Assumption 1, for each $\theta \in \Theta$, $\theta \in \Theta^*$ if and only if

$$\mathbb{E}[m(Y_i, X_i; b, \theta)|X_i = x] \geq 0 \ \forall b \in \mathbb{S}^{|\mathcal{Y}|-1}, \forall x \in \mathcal{X},$$

where

$$m(Y_i, x; b, \theta) \equiv -b^T \begin{pmatrix} \mathbb{1}\{Y_i = y^1\} \\ ... \\ \mathbb{1}\{Y_i = y^{|\mathcal{Y}|-1}\} \end{pmatrix} + \max_{P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x}} b^T \begin{pmatrix} P_{Y|X}(y^1|x) \\ ... \\ P_{Y|X}(y^{|\mathcal{Y}|-1}|x) \end{pmatrix}.$$

◇

Proposition 4 comes from the fact that, following BMM, one can express the condition $P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x}$ as

$$-b^T P^0_{Y|X}(\cdot|x) + \sup_{P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x}} b^T P_{Y|X}(\cdot|x) \geq 0 \ \forall b \in \mathbb{R}^{|\mathcal{Y}|}, \tag{6}$$

where the map

$$b \in \mathbb{R}^{|\mathcal{Y}|} \mapsto \sup_{P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x}} b^T P_{Y|X}(\cdot|x) \in \mathbb{R},$$

is the support function of $\bar{\mathcal{Q}}^{\theta}_{Y|x}$. Some simple algebraic manipulations reveal that (6) is equal to the collection of conditional moment inequalities above.

Second, Lemma 2 in AS shows that conditional moment inequalities can be transformed into equivalent unconditional moment inequalities by choosing appropriate instruments, $h \in \mathcal{H}$, where $\mathcal{H}$ is a collection of instruments and h is a function of X_i. In particular,

$$\theta \in \Theta^* \Leftrightarrow \mathbb{E}[m(Y_i, X_i; b, \theta, h)] \geq 0 \ \forall b \in \mathbb{S}^{|\mathcal{Y}|-1}, \forall h \in \mathcal{H} \text{ a.s.}, \tag{7}$$

where

$$m(Y_i, X_i; b, \theta, h) \equiv m(Y_i, X_i; b, \theta) \times h(X_i).$$

Further, observe that (7) is equivalent to

$$\theta \in \Theta^* \Leftrightarrow \min\left\{0, \min_{b \in \mathbb{S}^{|\mathcal{Y}|-1}} \mathbb{E}[m(Y_i, X_i; b, \theta, h)]\right\} = 0 \ \forall h \in \mathcal{H} \text{ a.s.}$$

In light of these remarks, BMM propose as test statistic

$$\text{TS}_n(\theta) \equiv \int_{\mathcal{H}} \min\left\{0, [\min_{b \in \mathbb{S}^{|\mathcal{Y}|-1}} \sqrt{n}\bar{m}_n(b, \theta, h)]^2\right\} d\Gamma(h),$$

where Γ is a probability measure on $\mathcal{H}$ as explained in Section 3.4 of AS, and

$$\bar{m}_n(b, \theta, h) \equiv \frac{1}{n} \sum_{i=1}^{n} m(Y_i, X_i; b, \theta, h).$$

Theorem B.2 in BMM shows that, under some regularity conditions, $\text{TS}_n(\theta)$ satisfies Assumptions S1-S4 and M2 of AS. This implies that AS's procedure is applicable. Moreover, given that the set $\mathcal{X}$ is finite, the analyst can use the uniform probability measure as suggested by Example 5 in Appendix B of AS. That is,

$$\text{TS}_n(\theta) \equiv \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \min \left\{ 0, [\min_{b \in \mathbb{S}^{|\mathcal{Y}|-1}} \frac{1}{\sqrt{n}} \sum_{i=1}^{n} m(Y_i, X_i; b, \theta) \mathbb{1}\{X_i = x\}]^2 \right\}. \tag{8}$$

In practice, to compute (8), the researcher should calculate, for each $x \in \mathcal{X}$,

$$\min_{b \in \mathbb{S}^{|\mathcal{Y}|-1}} \frac{1}{\sqrt{n}} \sum_{\substack{i \text{ s.t.} \\ X_i = x}} [-b^T \tilde{\mathbb{1}}_i + \max_{P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x}} b^T \tilde{P}_{Y|X}(\cdot|x)], \tag{9}$$

where $\tilde{\mathbb{1}}_i \equiv \begin{pmatrix} \mathbb{1}\{Y_i = y^1\} \\ \vdots \\ \mathbb{1}\{Y_i = y^{|\mathcal{Y}|-1}\} \end{pmatrix}$ and $\tilde{P}_{Y|X}(\cdot|x) \equiv \begin{pmatrix} P_{Y|X}(y^1|x) \\ \vdots \\ P_{Y|X}(y^{|\mathcal{Y}|-1}|x) \end{pmatrix}$. By rearranging terms, Expression (9) becomes

$$\min_{b \in \mathbb{S}^{|\mathcal{Y}|-1}} \max_{P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^{\theta}_{Y|x}} b^T [-\frac{1}{\sqrt{n}} \sum_{\substack{i \text{ s.t.} \\ X_i = x}} \tilde{\mathbb{1}}_i + \frac{n_x}{\sqrt{n}} \tilde{P}_{Y|X}(\cdot|x)], \tag{10}$$

where n_x is the number of observations featuring $X_i = x$. (10) is a min-max problem which can be simplified as follows. Note that the inner constrained maximisation problem in (10) is linear in $P_{Y|X}(\cdot|x)$. Thus, it can be replaced by its dual, which consists of a linear constrained minimisation problem. Moreover, the outer constrained minimisation problem in (10) has a quadratic constraint, $b^T b = 1$. Therefore, (10) can be rewritten as a quadratically constrained linear minimisation problem which is a tractable exercise. More details on this are in Appendix C. Once (10) is computed for each $x \in \mathcal{X}$, the analyst easily obtains $\text{TS}_n(\theta)$.

To compute the critical value, we follow AS's bootstrap method consisting of the following steps. Specifically, for each $x \in \mathcal{X}$, let

$$\bar{m}_n(b, \theta, x) \equiv \frac{1}{n} \sum_{i=1}^{n} m(Y_i, X_i; b, \theta) \mathbb{1}\{X_i = x\}.$$

We draw W_n bootstrap samples using nonparametric i.i.d. bootstrap. For each $w = 1, ..., W_n$, we compute

$$TS_{n,w}(\theta) \equiv \frac{1}{|\mathcal{X}|}\sum_{x\in\mathcal{X}} \min\left\{0, [\min_{b\in\mathbb{S}^{|\mathcal{Y}|-1}}(\sqrt{n}(\bar{m}^*_{n,w}(b,\theta,x) - \bar{m}_n(b,\theta,x)) + \varphi_n(b,\theta,x))]^2\right\},$$

where $\bar{m}^*_{n,w}(b,\theta,x)$ is calculated just as $\bar{m}_n(b,\theta,x)$, but with the bootstrap sample in place of the original sample, $\varphi_n(b,\theta,h) \equiv \mathbb{1}\{\frac{1}{\kappa_n}\sqrt{n}\bar{m}_n(b,\theta,h) > 1\} \times B_n$, and $\{\kappa_n\}_{n\in\mathbb{N}}$, $\{B_n\}_{n\in\mathbb{N}}$ are sequences of constants satisfying Assumption G.1 in AS. In particular, we use $\kappa_n \equiv (0.3\log(n))^{1/2}$ and $B_n \equiv \left(\frac{0.4\log(n)}{\log(\log(n))}\right)^{1/2}$ as suggested in Section 9 of AS. Lastly, $\hat{c}_{n,1-\alpha}(\theta)$ is the $(1-\alpha)$ sample quantile of $\{TS_{n,w}(\theta)\}_{w=1}^{W_n}$.

6 Conclusions

In this paper we consider a single-agent, static, discrete choice model in which agents can face attentional limits. This implies that decision makers may be uncertain about the payoffs generated by the available alternatives. Instead of explicitly modelling the information constraints, which can be susceptible to misspecification, we study identification and inference of the preference parameters while remaining agnostic about the mechanism determining the amount of information processed by decision makers. We exploit Theorem 1 in Bergemann and Morris (2016) to provide a tractable characterisation of the sharp identified set and study inference. Simulations of discrete choice models with risk aversion and Nested Logit models highlight that our methodology can produce informative bounds for the preference parameters.

We are currently working on an empirical illustration to real data.

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A Some remarks on Definition 1

We add some remarks on Definition 1. First, note that the product $P^i_{T|X,\epsilon,V}(t|x,e,v)P_{V|X,\epsilon}(v|x,e)$ in the inequality of Definition 1 is not DM i's posterior. However, by Bayes rule,

$$\sum_{v\in\mathcal{V}} u(y,x,e,v)P^i_{V|X,\epsilon,T}(v|x,e,t) \geq \sum_{v\in\mathcal{V}} u(\tilde{y},x,e,v)P^i_{V|X,\epsilon,T}(v|x,e,t),$$

if and only if

$$\sum_{v\in\mathcal{V}} u(y,x,e,v)P^i_{T|X,\epsilon,V}(t|x,e,v)P_{V|X,\epsilon}(v|x,e) \geq \sum_{v\in\mathcal{V}} u(\tilde{y},x,e,v)P^i_{T|X,\epsilon,V}(t|x,e,v)P_{V|X,\epsilon}(v|x,e),$$

provided that $\sum_{v\in\mathcal{V}} P^i_{T|X,\epsilon,V}(t|x,e,v)P_{V|X,\epsilon}(v|x,e)$ is different from zero.

Second, note that we can equivalently define an optimal strategy of the augmented choice problem (G,S_i) as follows. Given $x\in\mathcal{X}$, $e\in\mathcal{E}$, and $t\in\mathcal{T}_i$, let $\mathcal{Y}^i_{x,e,t}\subseteq\mathcal{Y}$ be the set of alternatives maximising DM i's expected payoff, i.e.,

$$\mathcal{Y}^i_{x,e,t} \equiv \text{argmax}_{y\in\mathcal{Y}} \sum_{v\in\mathcal{V}} u(y,x,e,v)P^i_{V|X,\epsilon,T}(v|x,e,t).$$

Let $\mathcal{P}^i_{x,e,t}$ be the family of probability mass functions of Y_i conditional on $(X_i,\epsilon_i,t_i)=(x,e,t)$ that are degenerate on each of element of $\mathcal{Y}^i_{x,e,t}$. Let $\text{Conv}(\mathcal{P}^i_{x,e,t})$ be the convex hull of $\mathcal{P}^i_{x,e,t}$. Then, $\mathcal{P}^i_{Y|X,\epsilon,T}$ is an optimal strategy of the augmented choice problem (G,S_i) if $P^i_{Y|X,\epsilon,T}(\cdot|x,e,t)\in\text{Conv}(\mathcal{P}^i_{x,e,t})$ $\forall x\in\mathcal{X}$, $\forall e\in\mathcal{E}$, and $\forall t\in\mathcal{T}_i$.

Third, note that Definition 1 allows to formally defines DM i's consideration set. In fact, following Caplin, Dean, and Leahy (2019), DM i's consideration set, $\mathcal{C}_i$, arises endogenously from $\mathcal{P}^i_{Y|X,\epsilon,T}$. In particular, $\mathcal{C}_i$ collects every alternative such that the subset of the signal's support inducing DM i to choose that alternative has positive measure. For example, when $\mathcal{T}_i$ is finite,

$$\mathcal{C}_i \equiv \{y\in\mathcal{Y} : \sum_{t\in\mathcal{T}_i} P^i_{Y|X,\epsilon,T}(y|x_i,e_i,t)\sum_{v\in\mathcal{V}} P^i_{T|X,\epsilon,V}(t|x_i,e_i,v)P_{V|X,\epsilon}(v|x_i,e_i)\},$$

where (x_i,e_i) are the realisations of (X_i,ϵ_i) assigned by nature to DM i.

B Proofs

Proof of Proposition 1 We proceed by construction. Take any $S_i\equiv(\mathcal{T}_i,\mathcal{P}^i_{T|X,\epsilon,V})\in\mathcal{S}$. First, note that the set $\mathcal{Y}$ is finite and, hence, compact. Second, the map $y\in\mathcal{Y}\mapsto u(y,x,e,v)\in\mathbb{R}$ is continuous using the discrete metric for each $x\in\mathcal{X}$, $e\in\mathcal{E}$, and $v\in\mathcal{V}$. Hence, the map $y\mapsto\sum_{v\in\mathcal{V}} u(y,x,e,v)P^i_{T|X,\epsilon,V}(t|x,e,v)P_{V|X,\epsilon}(v|x,e)$ is also continuous for each $x\in\mathcal{X}$, $e\in\mathcal{E}$, and $t\in\mathcal{T}_i$. Therefore, Weierstrass theorem ensures the existence of the minimum and maximum of such a map. Given $x \in \mathcal{X}$, $e \in \mathcal{E}$, and $t \in \mathcal{T}_i$, let $y^i_{x,e,t} \in \mathcal{Y}$ be one of the maximisers. Then, an optimal strategy is $\mathcal{P}^i_{Y|X,\epsilon,T}$ such that for each $x \in \mathcal{X}$, $e \in \mathcal{E}$, and $t \in \mathcal{T}_i$,

$$P^i_{Y|X,\epsilon,T}(y^i_{x,e,t}|x,e,t) = 1 \text{ and } P^i_{Y|X,\epsilon,T}(\tilde{y}|x,e,t) = 0 \ \forall \tilde{y} \in \mathcal{Y} \setminus \{y^i_{x,e,t}\}.$$

Proof of Proposition 2 Take any $\theta \in \Theta$ and $x \in \mathcal{X}$. We show that if $P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x}$, then $P_{Y|X}(\cdot|x) \in \bar{\mathcal{R}}^\theta_{Y|x}$. If $P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x}$, then, by definition of $\bar{\mathcal{Q}}^\theta_{Y|x}$, there exists $\mathcal{P}_{Y,V|X,\epsilon} \in \mathcal{Q}^\theta$ inducing $P_{Y|X}(\cdot|x)$. By Theorem 1, it follows that there exists $S \in \mathcal{S}$ and $\mathcal{P}_{Y|X,\epsilon,T} \in \mathcal{R}^{\theta,S}$ such that $\mathcal{P}_{Y|X,\epsilon,T}$ induces $\mathcal{P}_{Y,V|X,\epsilon}$. Thus, $\mathcal{P}_{Y|X,\epsilon,T}$ induces $P_{Y|X}(\cdot|x)$ by the transitive property. Therefore, by definition of $\bar{\mathcal{R}}^\theta_{Y|x}$, $P_{Y|X}(\cdot|x) \in \bar{\mathcal{R}}^\theta_{Y|x}$.

Conversely, we show that $P_{Y|X}(\cdot|x) \in \bar{\mathcal{R}}^\theta_{Y|x}$, then $P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x}$. First, let $\tilde{\mathcal{R}}^\theta_{Y|x} \subseteq \bar{\mathcal{R}}^\theta_{Y|x}$ be the non-convexified collection of probability mass functions of Y_i conditional $X_i = x$ that are induced by the model's optimal strategies under θ, while remaining agnostic about information structures. That is,

$$\tilde{\mathcal{R}}^\theta_{Y|x} \equiv \Big\{ P_{Y|X}(\cdot|x) \in \Delta(\mathcal{Y}) : \\ P_{Y|X}(y|x) = \int_{\mathcal{T}\times\mathcal{V}\times\mathcal{E}} P_{Y|X,\epsilon,T}(y|x,e,t) P_{T|X,\epsilon,V}(t|x,e,v) P^\theta_{V|X,\epsilon}(v|x,e) P^\theta_{\epsilon|X}(e|x) d(t,v,e) \ \forall y \in \mathcal{Y}, \\ \mathcal{P}_{Y|X,\epsilon,T} \in \mathcal{R}^{\theta,S}, S \in \mathcal{S} \Big\}.$$

Take $P_{Y|X}(\cdot|x) \in \tilde{\mathcal{R}}^\theta_{Y|x}$. Then, by definition of $\tilde{\mathcal{R}}^\theta_{Y|x}$, there exists $S \in \mathcal{S}$ and $\mathcal{P}_{Y|X,\epsilon,T} \in \mathcal{R}^{\theta,S}$ such that $\mathcal{P}_{Y|X,\epsilon,T}$ induces $P_{Y|X}(\cdot|x)$. By Theorem 1, it follows that there exists $\mathcal{P}_{Y,V|X,\epsilon} \in \mathcal{Q}^\theta$ inducing $\mathcal{P}_{Y|X,\epsilon,T}$. Thus, $\mathcal{P}_{Y,V|X,\epsilon}$ induces $P_{Y|X}(\cdot|x)$ by the transitive property. Hence, by definition of $\bar{\mathcal{Q}}^\theta_{Y|x}$, $P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x}$. Now, take any K elements from $\tilde{\mathcal{R}}^\theta_{Y|x}$, for any K. Denote such elements by $P^1_{Y|X}(\cdot|x) \in \tilde{\mathcal{R}}^\theta_{Y|x}, ..., P^K_{Y|X}(\cdot|x) \in \tilde{\mathcal{R}}^\theta_{Y|x}$. Given the arguments above, it holds that $P^1_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|X}(\cdot|x), ..., P^K_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x}$. Moreover, any convex combination of $P^1_{Y|X}(\cdot|x), ..., P^K_{Y|X}(\cdot|x)$ belongs to $\bar{\mathcal{Q}}^\theta_{Y|x}$ because $\bar{\mathcal{Q}}^\theta_{Y|x}$ is convex. Therefore, every $P_{Y|X}(\cdot|x) \in \bar{\mathcal{R}}^\theta_{Y|x}$ is also contained in $\bar{\mathcal{Q}}^\theta_{Y|x}$.

We can conclude that $\bar{\mathcal{R}}^\theta_{Y|x} = \bar{\mathcal{Q}}^\theta_{Y|x}$ $\forall \theta \in \Theta$ and $\forall x \in \mathcal{X}$. This implies $\Theta^* = \Theta^{**}$.

Proof of Proposition 3 Proposition 3 is obtained by combining Proposition 2 with Definition 2 to write explicitly $\bar{\mathcal{Q}}^\theta_{Y|x}$ for each $x \in \mathcal{X}$ and $\theta \in \Theta$.

Proof of Proposition 4 Fix any $\theta \in \Theta$ and $x \in \mathcal{X}$. Observe that

$$P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x} \ \Leftrightarrow \quad -b^T P^0_{Y|X}(\cdot|x) + \sup_{P_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x}} b^T P_{Y|X}(\cdot|x) \geq 0 \ \forall b \in \mathbb{R}^{|\mathcal{Y}|}. \tag{B.1}$$

By the positive homogeneity of the support function, $\forall b \in \mathbb{R}^{|\mathcal{Y}|}$,

$$-b^T P^0_{Y|X}(\cdot|x) + \sup_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} b^T P_{Y|X}(\cdot|x) \geq 0 \;\Leftrightarrow\; -\frac{b^T}{||b||} P^0_{Y|X}(\cdot|x) + \sup_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} \frac{b^T}{||b||} P_{Y|X}(\cdot|x) \geq 0. \tag{B.2}$$

By (B.2), (B.1) is equivalent to

$$P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x} \;\Leftrightarrow\; -b^T P^0_{Y|X}(\cdot|x) + \sup_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} b^T P_{Y|X}(\cdot|x) \geq 0 \;\forall b \in \mathbb{S}^{|\mathcal{Y}|}. \tag{B.3}$$

Moreover, given that $\bar{\mathcal{Q}}^\theta_{Y|x}$ is closed and bounded, (B.3) is equivalent to

$$P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x} \;\Leftrightarrow\; -b^T P^0_{Y|X}(\cdot|x) + \max_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} b^T P_{Y|X}(\cdot|x) \geq 0 \;\forall b \in \mathbb{S}^{|\mathcal{Y}|}. \tag{B.4}$$

Lastly, given that $\bar{\mathcal{Q}}^\theta_{Y|x}$ is a subset of the $(|\mathcal{Y}|-1)$-dimensional simplex, (B.4) is equivalent to

$$P^0_{Y|X}(\cdot|x) \in \bar{\mathcal{Q}}^\theta_{Y|x} \;\Leftrightarrow\; -b^T \begin{pmatrix} P^0_{Y|X}(y^1|x) \\ \vdots \\ P^0_{Y|X}(y^{|\mathcal{Y}|-1}|x) \end{pmatrix} + \max_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} b^T \begin{pmatrix} P_{Y|X}(y^1|x) \\ \vdots \\ P_{Y|X}(y^{|\mathcal{Y}|-1}|x) \end{pmatrix} \geq 0 \;\forall b \in \mathbb{S}^{|\mathcal{Y}|-1}. \tag{B.5}$$

Therefore, by combining Proposition 2 with (B.5), we get that

$$\theta \in \Theta^* \Leftrightarrow -b^T \begin{pmatrix} P^0_{Y|X}(y^1|x) \\ \vdots \\ P^0_{Y|X}(y^{|\mathcal{Y}|-1}|x) \end{pmatrix} + \max_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} b^T \begin{pmatrix} P_{Y|X}(y^1|x) \\ \vdots \\ P_{Y|X}(y^{|\mathcal{Y}|-1}|x) \end{pmatrix} \geq 0 \;\forall b \in \mathbb{S}^{|\mathcal{Y}|-1}, \tag{B.6}$$

which is equivalent to

$$\theta \in \Theta^* \Leftrightarrow \mathbb{E}[m(Y_i, X_i; b, \theta | X_i = x)] \geq 0 \;\forall b \in \mathbb{S}^{|\mathcal{Y}|-1},$$

as claimed in Proposition 4.

C Inference: some computational simplifications

Fix any $\theta \in \Theta$ and $x \in \mathcal{X}$. Recall Expression (10), which we report here

$$\min_{b\in\mathbb{S}^{|\mathcal{Y}|-1}} \max_{P_{Y|X}(\cdot|x)\in\bar{\mathcal{Q}}^\theta_{Y|x}} b^T\Big[-\frac{1}{\sqrt{n}} \sum_{\substack{i \text{ s.t.} \\ x}} \tilde{\mathbb{1}}_i + \frac{n_x}{\sqrt{n}} \tilde{P}_{Y|X}(\cdot|x)\Big]. \tag{C.1}$$

By using Definition 2 to write explicitly the feasible set $\bar{\mathcal{Q}}^{\theta}_{Y|x}$, (C.1) is equivalent to

$$
\begin{aligned}
\min_{b\in\mathbb{R}^{|\mathcal{Y}|-1}} \quad & \max_{\substack{P_{Y|X}(\cdot|x)\,\in\,\mathbb{R}_+^{|\mathcal{Y}|}\\ P_{Y,V|X,\epsilon}(\cdot|x,e)\,\in\,\mathbb{R}_+^{|\mathcal{Y}|\cdot|\mathcal{V}|},\forall e\in\mathcal{E}}} \quad b^T[-\frac{1}{\sqrt{n}}\sum_{\substack{i \text{ s.t.}\\ x}} \tilde{\mathbb{1}}_i + \frac{n_x}{\sqrt{n}}\tilde{P}_{Y|X}(\cdot|x)],\\
\text{s.t.} \quad & [b\in\mathbb{S}^{|\mathcal{Y}|-1}]: \quad b^T b = 1,\\
& [\text{1BCE-Consistency}]: \quad \sum_{y\in\mathcal{Y}} P_{Y,V|X,\epsilon}(y,v|x,e) = P_{V|\epsilon,X}(v|e,x)\ \forall v\in\mathcal{V},\forall e\in\mathcal{E},\forall x\in\mathcal{X},\\
& [\text{1BCE-Obedience}]: \quad -\sum_{v\in\mathcal{V}} P_{Y,V|X,\epsilon}(y,v|x,e)[u(y,x,e,v)-u(y',x,e,v)]\leq 0\ \forall y\in\mathcal{Y},\forall y'\in\mathcal{Y}\setminus\{y\},\forall e\in\mathcal{E},\forall x\in\mathcal{X},\\
& [\text{1BCE-model predictions}]: \quad P_{Y|X}(y|x) = \sum_{(e,v)\in\mathcal{E}\times\mathcal{V}} P_{Y,V|X,\epsilon}(y,v|x,e)P_{\epsilon|X}(e|x)\ \forall y\in\mathcal{Y},\forall x\in\mathcal{X}.
\end{aligned}
\tag{C.2}
$$

We simplify (C.2) by introducing new variables. Let

$$
\mathbb{1}_i \equiv \begin{pmatrix} \mathbb{1}\{Y_i = y^1\} \\ \vdots \\ \mathbb{1}\{Y_i = y^{|\mathcal{Y}|}\} \end{pmatrix},
$$

and

$$
Z_1 \equiv -\frac{1}{\sqrt{n}}\sum_{\substack{i \text{ s.t.}\\ X_i = x}} \mathbb{1}_i + \frac{n_x}{\sqrt{n}}P_{Y|X}(\cdot|x).
$$

Note that Z_1 is a $|\mathcal{Y}|\times 1$ vector. Further, let Z_2 be the $(|\mathcal{Y}|\cdot|\mathcal{V}|\cdot|\mathcal{E}|)\times 1$ vector collecting $P_{Y,V|X,\epsilon}(\cdot|x,e)$ across every $e\in\mathcal{E}$. Lastly, let Z be the $(|\mathcal{Y}|+|\mathcal{Y}|\cdot|\mathcal{V}|\cdot|\mathcal{E}|)\times 1$ vector collecting Z_1 and Z_2. (C.2) can be rewritten as

$$
\begin{aligned}
\min_{b\in\mathbb{R}^{|\mathcal{Y}|-1}} \quad & \max_{\substack{Z_1\,\in\,\mathbb{R}^{|\mathcal{Y}|}\\ Z_2\,\in\,\mathbb{R}_+^{|\mathcal{Y}|\cdot|\mathcal{V}|\cdot|\mathcal{E}|}}} \begin{bmatrix} b^T & 0 & 0^T_{|\mathcal{Y}|\cdot|\mathcal{V}|\cdot|\mathcal{E}|}\end{bmatrix} Z,\\
\text{s.t.} \quad & b^T b = 1,\\
& A_{\text{eq}}\ Z = B_{\text{eq}},\\
& A_{\text{ineq}}\ Z \leq 0_{d_{\text{ineq}}},
\end{aligned}
\tag{C.3}
$$

where A_{eq} is the matrix of coefficients multiplying Z in the equality constraints of (C.2) with d_{eq} rows, B_{eq} is the vector of constants appearing in the equality constraints of (C.2), and A_{ineq} is the matrix of coefficients multiplying Z in the inequality constraints of (C.2) with d_{ineq} rows.

Further, the inner constrained maximisation problem in (C.3) is linear. Hence, by strong duality, can be replaced with its dual. This allows us to solve one unique minimisation problem.

Precisely, the solution of (C.3) is equivalent to the solution of

$$
\begin{aligned}
\min_{\substack{b \in \mathbb{R}^{|\mathcal{Y}|-1} \\ \lambda_{\text{eq}} \in \mathbb{R}^{d_{\text{eq}}} \\ \lambda_{\text{ineq}} \in \mathbb{R}_{+}^{d_{\text{ineq}}}}} \quad & \begin{bmatrix} B_{\text{eq}}^T & 0_{d_{\text{ineq}}}^T \end{bmatrix} \lambda, \\
\text{s.t.} \quad & b^T b = 1, \\
& [A^T]_{1:|\mathcal{Y}|} \lambda = \begin{pmatrix} b \\ 0 \end{pmatrix}, \\
& [A^T]_{|\mathcal{Y}|+1:|\mathcal{Y}|+|\mathcal{Y}|\cdot|\mathcal{V}|\cdot|\mathcal{E}|} \lambda \geq 0_{|\mathcal{Y}|\cdot|\mathcal{V}|\cdot|\mathcal{E}|},
\end{aligned}
\tag{C.4}
$$

where λ is the $(d_{\text{eq}} + d_{\text{ineq}}) \times 1$ vector collecting λ_{eq} and λ_{ineq}, A is the $(d_{\text{eq}} + d_{\text{ineq}}) \times (|\mathcal{Y}| + |\mathcal{Y}| \cdot |\mathcal{V}| \cdot |\mathcal{E}|)$ matrix obtained by stacking one on top of the other the matrices A_{eq} and A_{ineq}, and $[A]_{i:j}$ denotes the sub-matrix of A containing the rows $i, i+1, ..., j$ of A.

Note that (C.4) is a quadratically constrained linear minimisation problem. In particular, the first constraint in (C.4) is quadratic. The objective function and the remaining constraints in (C.4) are linear.

Close derivations are discussed in Magnolfi and Roncoroni (2017) for an entry game setting.