Direct Preference Elicitation Over Public Outcomes

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Abstract

I apply implementation theory to study the design of experiments that elicit subject preferences over public outcomes. Any experiment in which preferences can be inferred from dominant strategies is outcome equivalent to a direct preference elicitation experiment in which subjects directly state their preferences and the outcome is chosen according to a strategy-proof social choice function. While all strategy-proof social choice functions make truthful reporting a dominant strategy, the strength of incentives differ. A design called *Random Dictator over Pairs* [RDP] provides the strongest incentives to truthfully report an entire rank-ordering for any set of subject beliefs.

I Introduction

Lab experiments are often used by economists to measure subject preferences over various kinds of outcomes. These outcomes may be purely private as in study of risk preferences or time preferences[1]. The focus of this paper is eliciting preferences when the outcomes are public. In addition to the large literature on social preference and distributional preference[2], examples include preferences over who contributes to a public good (Bergstrom et al., 2015), or which set of rules to use in playing a game (Dal Bó et al., 2015).

The goal of the experimenter is to truthfully elicit unknown preferences. Unknown preferences also play a central role in mechanism design. The goal of a mechanism designer is to implement a particular set of contingent outcomes (also known as a *social choice function*[3]) as the equilibrium of a game. However, when a social choice function can be implemented as the equilibrium of *any* game, it can be implemented as a truthful equilibrium of a game which *directly elicits preferences* and chooses the desired contingent outcome. This is the celebrated *revelation principle* (Gibbard, 1973).

This fact is relevant to the experiment designer as well. Any implementable social choice function can be used to truthfully and *directly* elicit unknown preferences. When used in the context of experiment design, I refer to implementable[4] social choice functions as *direct elicitation methods.* However, while any direct elicitation method makes truth-telling

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[1] See for instance Kagel et al. (1995); Holt et al. (2002); Andersen et al. (2008); Andreoni and Sprenger (2012a,b).

[2] See for instance Andreoni and Miller (2002); Engelmann and Strobel (2004); Fisman et al. (2007); Chen and Li (2009).

[3] A mapping from preference profiles into outcomes.

[4] Throughout the paper I focus on strategy-proof implementation.

a dominant strategy, the strength of incentives may differ. For instance, while randomly choosing an outcome is a strategy-proof SCF, the incentives are weak. Subjects are indifferent between submitting any preference ranking. *Random Dictator* (choosing a subject at random and implementing their favorite outcome) provides strong incentives for each player to correctly rank their favorite outcome but are otherwise weak.

The problem of the experiment designer in this setting is to choose the particular direct elicitation method that provides the most desirable set of incentives. I suggest a solution to this problem for instances when the experimenter has no strong prior about subject preferences and beliefs. The result is a generalized experiment design for eliciting ordinal preferences over public outcomes.

The proposed design is *Random Dictator over Pairs [RDP]***.** Subjects submit rank-ordered lists over public outcomes. One subject and a pair of outcomes is chosen randomly (with uniform probability). The outcome implemented is the one that the chosen subject ranks highest from the chosen pair. *RDP* has the property that it elicits truthful preferences regardless of subjects' beliefs (it is strategy-proof) and among all direct elicitation methods, it provides the strongest incentives against non-truthfully swapping the even most weakly incentivized pair of outcomes over all players and possible preference profiles.

I also discuss modifications of *RDP* to deal with instances where the experimenter is interested in providing stronger incentives for subjects to reveal preferences near the top of their rank-order list. This analysis demonstrates an important non-linear trade-off between the strength of incentives and how those incentives are spread over the rank-order list. *RDP* settles this in one extreme, spreading the incentives as evenly as possible to collect information about the entire rank order. A classic alternative, **Random Dictator [*RD*]**, settles this at the other extreme, concentrating incentives at the top of the rank-order list but providing much stronger incentives there. I propose a generalized design which nests both *RDP and RD.* I also show that *RDP* is robust to preference intransitives.

This paper is organized as follows, section II presents the general theoretical environment, as well as examples of direct elicitation methods. Section III proves the robust optimality of *RDP* and discusses extensions. Section V provides examples of applications and a concludes.

II Environment

A Environment and Definitions

V is a finite set of public alternatives. n players each have preferences over V- a total-ordering represented by the ranking P. $\mathbf{P}$ is ranking-profile, a vector of n rankings $\mathbf{P} = (P_1, P_2, ..., P_n)$. $\left(\tilde{P}, \mathbf{P}_{-i}\right)$ is a ranking-profile in which all but the ith element are identical to that in $\mathbf{P}$ and the ith element is $\tilde{P}$. $\mathbf{P}^{ky}$ is a profile generated from $\mathbf{P}$ by raising the outcome y up by one position in k's ranking.

Each player assigns a cardinal utility to every member of V represented by the Bernoulli utility function $U(x)$ where $x \in V$. This is extended to a VNM utility function by assigning for any lottery ρ over V, $U(\rho) = \sum_{x \in V} U(x)\rho(x)$.

A **social-choice function** d is a assigns each $\mathbf{P}$ a lottery over V denoted $d(P)$. A strategy-proof social-choice function is one for which there is no U $\mathbf{P}$,$\tilde{P}$ such that: $U\left(d\left(\tilde{P}, \mathbf{P}_{-i}\right)\right) > U\left(d\left(P, \mathbf{P}_{-i}\right)\right)$.

If the experiment designer is interested in truthfully and robustly (with regards to the player's beliefs) eliciting preferences, then any strategy-proof social choice function is sufficient. Designing an experiment in this environment amounts to choosing a strategy-proof social choice function. Because of this equivalence, I refer to strategy-proof social choice functions as **Direct Elicitation Methods.** Below are several examples of direct elicitation methods.

Random Choice *[RC]: An outcome is chosen randomly.*

Random Dictator *[RD]: A single player i is chosen randomly. The implemented outcome is the one i ranks first.*

Majority over Random Pairs *[MRP]: A pair of outcomes is chosen at random. The implemented outcome is the one that a majority rank higher. (With ties broken randomly.)*

Random Dictator over Pairs *[RDP]: A pair of outcomes and a single player i are chosen randomly. The implemented outcome is the one that i ranks higher from the pair.*

These examples demonstrate the potential incentive shortcomings of alternative elicitation methods. *Random dictator* provides strong incentives for each player to list their top outcome truthfully. However, the incentives for listing outcomes below the top are weak. Players are indifferent between submitting any ranking which correctly positions their top choice. In *Majority over Random Pairs,* reporting truthfully is also dominant. However, the strength of incentives depend on beliefs. For instance, if a player thinks everyone else will submit the same ranking, then she is indifferent between submitting all rankings.

RDP appears to overcome all of these shortcomings. As long as players are not indifferent between outcomes, then they are not indifferent between submitting any ranking, regardless of their beliefs. Informally, *RDP* appears to be a desirable solution when the goal is to elicit the entire ranking in a robust way, rather than just the top ranked outcome or the entire ranking with belief dependent incentives. To formalize this, I start by providing Gibbard's characterization of strategy-proof social choice functions *(Gibbard, 1977)*.

B Characterizing Direct Elicitation Methods

The following two requirements are necessary and sufficient for a social choice function to be strategy-proof *(Gibbard, 1977)*:

Pairwise-Responsive: *social choice functions for which one player swapping two adjacent outcomes affects only the probabilities of those outcomes.*

Non-Perverse**:** *social choice functions for which swapping a single outcome upwards in a player's preferences cannot decrease the probability of that outcome being chosen.*

Theorem 1. *Gibbard (1977) Characterization*: a social choice function is strategy-proof if and only if it is pair-wise responsive and non-perverse.

The next result provides the ingredients for building strategy-proof social choice functions. They are all mixtures[5] of two simple types of rules:

Unilateral rules*: social choice functions that depend only on a single player's preferences.*
Duple rules*: social choice function which choose between a pair of outcomes.*

Theorem 2. *Gibbard (1977) Mixture*: a social choice function is strategy-proof only if and only if it is a mixture of pair-wise responsive and non-perverse social choice functions that are all either unilateral or duple rules.

Referring back to the examples, *Random Choice* is mixture over unilateral rules where each outcome set is a singleton. *Random Dictator* is a mixture over unilateral rules where each outcome set is the entire set V. *Majority over Random Pairs* is a mixture over the duple rules which decide each possible pair using the majority rule (a pairwise responsive and non-perverse rule). *Random Dictator over Pairs* is a mixture over unilateral rules where each outcome set is a pair.

Other, more exotic rules exist in the set as well. For instance: randomly choose a subset of A. If the subset is a pair, choose by majority rule, otherwise choose by random dictator. In addition, any mixtures of the rules mentioned above is also a direct elicitation method.

III Choosing an Elicitation Method

A Optimal Robust Elicitation

Since the designer is neutral with regard to players' cardinal utilities, her objective function is ordinal. Let $d_y(P)$ denote the probability assigned by $d(P)$ to outcome $y \in V$ and let $\epsilon_k^y(d, \mathbf{P}) = d_y(\mathbf{P}^{ky}) - d_y(\mathbf{P})$ for any y that is not ranked at the top of k's list. This is the probability increase for outcome y if player k moves y up by one position in her ranking. Another way to think about ϵ is the probability that a player will receive her less desired outcome from a pair if she accidentally swaps that pair in her reported order. Higher values of ϵ represent stronger incentives. For instance, if d is *random choice* $\epsilon_k^y(d, \mathbf{P}) = 0$ everywhere, since preference reports are ignored. In a scenario with only one player and two outcomes where d chooses the player's favorite reported outcome $\epsilon_k^y(d, \mathbf{P}) = 1$. Falsely swapping preferences will always result in the undesirable outcome. With n players, where d is *random dictator*, $\epsilon_k^y(d_l, \mathbf{P}) = \frac{1}{n}$ for y that is ranked second in a player's list, but 0 elsewhere.

When the designer wishes to elicit an entire ranking, and has no strong prior about the distribution of $\mathbf{P}$ or player's beliefs about $\mathbf{P}$,it is reasonable to focus on the worst case scenario incentives. In this case, her objective is to maximize the minimum value of ϵ_k^y over all players, outcomes and preference profiles. That is, the designer's goal is to find a rule d^* which solves: $Max_{d\in\mathcal{D}}\left[Min_{k,y,\mathbf{P}}\epsilon_k^y(d, \mathbf{P})\right]$. I refer to any rule which solves this problem *as* ***Robustly Optimal.*** Below, I show that *RDP* is a robustly optimal rule. The proof is rather straight-forward, the following lemma establishes an upper bound for $Min_{k,y,\mathbf{P}}\epsilon_k^y(d, \mathbf{P})$ which I then show to be met by *RDP.*

[5]Formally d is mixture of k social choice functions $\{d_1, d_2, ...d_k\}$ if there are positive weights $(w_1, w_2, ...w_k)$ summing to 1 such that $d = w_1 d_1 + w_2 d_2 + ...w_k d_k$

Lemma. $Min_{k,y,\mathbf{P}}\epsilon_k^y(d,\mathbf{P}) \leq \frac{2}{n(m-1)m}$.

Proof. Denote $Min_{k,y,\mathbf{P}}\epsilon_k^y(d,\mathbf{P}) = \tilde{\epsilon}$ and suppose $\tilde{\epsilon} > \frac{2}{n(m-1)m}$ and so any $\epsilon_k^y(d,\mathbf{P}) > \frac{2}{n(m-1)m}$. Start from a profile $\mathbf{P_0}$ where player's rank the outcomes identically such that the ranking of any player is $(y_1, y_2, y_3, ..., y_m)$. Now raise y_m to the top of each player's ranking to get $\mathbf{P}_1$. In making this change, y_m has been raised by $m-1$ positions in each of n player's rankings, increasing the probability of the outcome y_m by at least $(m-1)n$ times $\tilde{\epsilon}$. Thus, $d_{y_m}(\mathbf{P}_1) > \frac{2}{n(m-1)m}(m-1)n = \frac{2}{(m-1)m}(m-1)$. Now starting from $\mathbf{P}_1$, raise y_{m-1} up in every player's ranking until it is below y_m. Let $\mathbf{P}_2$ denote the new profile of rankings. By pairwise-responsiveness, $d_{y_m}(\mathbf{P}_2) = d_{y_m}(\mathbf{P}_1)$. By an analogous argument to that above, $d_{y_{m-1}}(,\mathbf{P}_2) > \frac{2}{n(m-1)m}(m-2)n = \frac{2}{(m-1)m}(m-2)$. Continuing in this way for each successive $y_{m-2}, y_{m-3}, ..., y_1$. The final profile $\mathbf{P}_m$ has the outcomes reversed with respect to the original $\mathbf{P_0}$.

Under the final profile of rankings, $d_{y_m}(\mathbf{P}_m) > \frac{2}{(m-1)m}(m-1)$, $d_{y_{m-1}}(\mathbf{P}_m) > \frac{2}{(m-1)m}(m-2), d_{y_{m-2}}(P_m) > \frac{2}{(m-1)m}(m-3), ..., d_{y_1}(\mathbf{P}_m) > 0$. Summing over these inequalities yields the following $\sum_{i\in V} d_i(\mathbf{P}_m) > 1$, a contradiction since d is a lottery over V. □

Proposition 3. *(RDP is Robustly Optimal.)*

Proof. In RDP, raising an outcome y up one position only changes the outcome if the player is randomly chosen as dictator which happens with probability $\frac{1}{n}$. Conditional on being chosen, raising y up one position only changes the outcome when the pair of outcomes randomly chosen is y and the outcome now immediately below y (previously above y) since this is the only outcome for which y's relative position has changed. This probability these two outcomes are chosen is $\frac{2}{m(m-1)}$. The change in probability for increasing y by one position $\epsilon_k^y(d,\mathbf{P}) = \frac{2}{nm(m-1)}$ for any $y,\mathbf{P},k$. Thus, the $Min_{k,y,\mathbf{P}}\epsilon_k^y(d,\mathbf{P}) = \frac{2}{n(m-1)m}$. Since RDP attains the upper bound, it is optimal. □

IV Intransitive Preferences

There is a substantial body of experimental work demonstrating transitivity violations in subject data. The analysis above assumes a cardinal utility function- not compatible with intransitive preferences. In this section, I extend the analysis of procedures to elicit potentially intransitive preference relations.

A Ordinal Environment

The objects of interest in this section are binary preference relations. A profile of preference relations for all players is denoted $\succ$ and $\succ_{-i}$ is given the usual meaning. Let $\mathcal{S}_i$ be the set of all asymmetric relations on V (the set of outcomes) and $\mathcal{S} = \times_{i-1}^n \mathcal{S}_i$. An **ordinal social-choice function** d assigns every $\succ \in \mathcal{S}$ a lottery over V denoted $d(\succ)$.

Familiar social-choice functions in this ordinal environment must be suitably redefined. For instance, in the cardinal environment, *Random Dictator* chooses the maximal element from a players preference ordering. However, a maximal element might not exist with intransitive preferences, such as in example 5 below. One way to generalize random dictator to the ordinal environment is to choose a dictator and an element from the top-cycle of that dictators preferences. A top-cycle is a set of outcomes $T \subseteq V$ such that for all $x \in T$ and all $y \in V/T$, $x \succ_i y$. If $\succ_i$ is transitive, then the set T is a singleton, the maximal element. In example 5 below, I refer to this social choice function as *ordinal random-dictator.*

There is a further complication in extending preferences about V to preferences about lotteries over V and defining a suitable notion of strategy-proofness. Here, I focus on generalizing the conditions which are necessary and sufficient for strategy-proofness in the caridnal setting.

Ordinal Pairwise-Responsive: *social choice functions for which one player swapping a single pair $x \succ_i y$ to $y \succ_i x$ affects only the probabilities of x and y.*

Ordinal Non-Perverse**:** *social choice functions for which one player swapping a single pair $x \succ_i y$ to $y \succ_i x$ does not strictly decrease the probability of y.*

It is noted that when restricted to transitive preference orderings, these requirements are identical to the necessary and sufficient conditions for strategy-proofness from Gibbard (1977). Instead of defining and characterizing an ordinal notion of strategy-proofness, here I simply define ordinal strategy-proof using these two generalized properties.

Definition 4. An ordinal social choice function d is **Ordinal Strategy-Proof** if and only if it is *ordinal pairwise-responsive* and *ordinal non-perverse*.

Example 5. (*Ordinal Random Dictator* is not Ordinal Strategy-Proof).
Suppose $n = 2$ and $V = \{x, y, z\}$. Player one has cyclic preferences $x \succ_1 y$, $y \succ_1 z$, $z \succ_1 x$ and player two has transitive preferences $x \succ_2 y$, $y \succ_2 z$, $x \succ_2 z$. Under truthful reporting, x, y, z are all in the top-cycle of $1's$ preferences. Thus, if 1 is chosen as dictator, one of these three will be chosen at random. On the other hand, x is the only element of 2's top-cycle. Thus, under truthful reporting, the probability that x is chosen is $\frac{2}{3}$ the probability y is chosen is $\frac{1}{6}$ and the probability z is chosen is $\frac{1}{6}$.
If player 1 instead reports the profile $\tilde{\succ}_1$: $x\tilde{\succ}_1 y$, $y\tilde{\succ}_1 z$, $x\tilde{\succ}_1 z$ (by swapping only the relation on the pair x, z) then the probability x is chosen is 1. Since the probability that y is chosen also changes, this demonstrates that the rule is not ordinal pariwise-responsive.

Definition 6. Ordinal Random Dictator over Pairs [$ORDP$].
Ordinal Random Dictator over Pairs randomly selects (uniformly) an $i \in \{1, ..., n\}$ and pair of (non-identical) outcomes x, y. It implements the outcome (either x or y) that is preferred according to reported preferences $\succ_i$.

Proposition 7. *ORDP is Ordinal Strategy-Proof.*

Proof. *Let $p_{i,\{x,y\}}$ be the probability that i is chosen as dictator and $\{x, y\}$ as the random pair. For a particular i and $\succ$ assume without loss of generality that $x \succ_i y$. If the relation on x and y are swapped by player i then the probability that y is chosen increases by $p_{i,\{x,y\}}$. The probability x is chosen decreases by the same amount. Thus, the rule is ordinal non-perverse. Since no other outcomes are affected, the rule is ordinal pairwise-responsive.* □

Thus, in addition to being robust in cardinal environments, RDP provides robust incentives against falsely changing elements of the binary relation $\succ_i$ even when that relation is intransitive. Of course to learn about potentially intransitive, the binary relation $\succ_i$ must be elicited, rather than the ranking P_i. In instances where $\succ_i$ is transitive, *ORDP* is equivalent to *RDP*.

V Discussion

A Applications

Below is a brief selection of potential applications of the direct elicitation methods discussed here.

Preferences over Games

An application related to Dal Bó et al. (2015) regards eliciting preferences over which type of game players would like to engage in. Dal Bó et al. (2015) have player's selecting between two games. They use both random dictator and majority rules. Since there are only two outcomes in their experiment, both are strategy-proof. To extend such an experiment to elicit player's full rank-order over three or more games, *RDP* is a natural direct elicitation method.

On the other hand , *RDRS-l* would be a natural design if there are many possible games, and only a subset of the rank-ordering is of interest. For instance, if the experimenter is interested in learning about each player's top three games from a set of 10 then *RDRS*-8 (choosing a random dictator's favorite outcome over a random set of 8 games) provides stronger incentives for correctly revealing the top three for each player while making them indifferent in ranking the bottom seven. As discussed above, since the ranking below the top three is irrelevant, it would be practical to only ask player's to rank their top three.

Preferences Over Gender Composition of Tournament Teams

There is a growing literature about gender-differences in competitive environments (for a review, see Niederle and Vesterlund, 2011). Healy and Pate (2011) find that women prefer to compete in teams of two while men prefer to compete as individuals in an adding task. Suppose an experimenter is interested in how men and women differ in their preferences over the gender compositions of teams they will compete in and compete against in tournaments involving teams of three. There are ten possible partitions of six players (three male and three female) into teams of three. The experimenter can use *RDP* to elicit each player's preferences over the ten possible match-ups and measure the differences in the types of teams men and women prefer to be on and the teams they prefer to compete against.

If it is of particular interest how the all-male against all-female team ranks, this can be included in all choice sets (as discussed in section B). To check for demand effect caused by this asymmetry, it is advisable to check against a separate data-set which does not up-weight the same-gender matches.

B Conclusion

In this paper, I have provided several results useful to researchers designing experiments to elicit preferences over public outcomes. In these instances it is possible to directly elicit preferences by using any strategy-proof social choice function (which I refer to as direct elicitation methods) as the outcome function. Under direct elicitation, the incentives for truthful reporting are transparent to subjects and easy to analyze for the designer. Direct elicitation is most appropriate when the primary goal of an experiment is the straightforward elicitation of ordinal preferences. At times, it is desirable to elicit preferences within the context of a particular game. In those cases, the methods discussed here may not be appropriate.

VI Appendix

A *Rank-Weighted Elicitation*

RDP provides the strongest possible incentives across a player's entire ranking of outcomes. In certain experimental contexts, the entire list may not be of interest. For instance, the experimenter may be most interested in player's favorite outcomes. As discussed above, *random dictator* provides very strong incentives for players to truthfully report their favorite outcome, but sacrifices incentives to truthfully report outcomes below the top. It is also possible to provide incentives that are "intermediate" to these two extremes by using choice sets that are larger than pairs (*RDP*) and smaller than the entire set V (*RD).*

Random Dictator over l-Restricted Sets *[RDRS-l]: A subset of V with cardinality l and a single player i are chosen randomly. The implemented outcome is the one that i ranks higher from the chosen set.*

This is a direct elicitation method since it is a mixture of pairwise-responsive and non-perverse unilateral rules. It nests both *RDP* and *RD.* Using a large l strengthens incentives at the top of player's rank-orders while using small l spreads the incentives. Where d_l is *RDRS-l,* and p is the location of y in P_k:

$$\epsilon_k^y(d_l, \mathbf{P}) = \frac{1}{n}\frac{(l)!\,(m-l)!}{m!}\binom{m-p}{l-2}$$

An example for $m = 6$ and $n = 2$ is provided below. Notice that much stronger incentives can be provided when outcomes only near the top of each ranking are required. This is a result of the combinatorial nature of the problem. In order to get accurate information about an entire rank-order, all possible $\frac{m(m-1)}{2}$ pairs must be potentially sampled. However, to get accurate information only about the top of a player's list, only the entire set V needs to be sampled. Notice that in the table below with $m = 6$, $\frac{m(m-1)}{2} = 15$. The incentives provided at the top of the rank list for *RD* is exactly 15 times larger than the incentives at any position in *RDP.* This non-linear trade-off represents an important consideration in experimental design.

	$l = 2$	3	4	5	6
$p = 2$ (*RDP*)	0.022	0.022	0.022	0.022	0.022
$p = 3$	0.067	0.050	0.033	0.017	0
$p = 4$	0.133	0.067	0.022	0	0
$p = 5$	0.222	0.056	0	0	0
$p = 6$ (*RD*)	0.333	0	0	0	0

Table 1: ϵ_k^y for *RDRS-l* with $n = 3$, $m = 6$

A practical extension of this method, especially where m is large, is to ask players to rank only their top $(m - 1) - l$ outcomes. Since in any random choice set *RDRS-l* will always include at least one item in a player's top $(m - 1) - l$, the way outcomes ranked below this are irrelevant.

B Outcome-Weighted Elicitation

In some contexts, the experimenter may be interested in where a particular outcome, or a subset of outcomes, fall in a player's ranking. Here, the experimenter would like to provide stronger incentives to correctly rank these outcomes. This is possible using *RD*P but weighting the random selection of choice-sets such the the outcomes of interest are included more often. For example, by always including particular outcome y in the choice-pair, $\epsilon_k^y(d, \mathbf{P}) = \frac{1}{n}\frac{1}{m-1}$. Thus, the incentives for correctly ranking y are $\frac{m}{2}$ times larger than *RDP*. However, as a trade-off players are indifferent in how they position two adjacent outcomes that do not include y.

More complicated hybrids of outcome-weighted and rank-weighted methods are also possible. A practical concern for using outcome-weighted elicitation is that breaking the symmetry of the elicitation method might create a demand effect, skewing how players rank the up or down-weighted outcomes. However, t is possible to use standard *RDP* as a baseline to check for these effects.

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