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Interpreting the Will of the People
A Positive Analysis of Ordinal Preference Aggregation

Abstract

We investigate how individuals think groups should aggregate members' ordinal preferences -that is, how they interpret "the will of the people." In an experiment, we elicit revealed attitudes toward ordinal preference aggregation and classify subjects according to the rules they apparently deploy. Majoritarianism is rare. Instead, people employ rules that place greater weight on compromise options. The classification's fit is excellent, and clustering analysis reveals that it does not omit important rules. We ask whether rules are stable across domains, whether people impute cardinal utility from ordinal ranks, and whether attitudes toward aggregation differ across countries with divergent traditions.

JEL-Codes: C910, D710.

Keywords: preference aggregation, experiment, social welfare analysis.

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1 Introduction

Envision a benevolent party (the planner) who must make a decision that impacts the members of some group, and who possesses accurate information about the group members' preferences. The foundational question of *social welfare* asks, how should the planner determine what is best for the group? Potential answers to this question have been the subject of enduring debate since at least the late 18th century, when Marie Jean Antoine Nicholas Caritat, better known as Marquis de Condorcet, and Jean-Charles de Borda proposed the competing aggregation criteria that still bear their names (Borda, 1781; Condorcet, 1785). Condorcet advocated selecting an option that majority-defeats all alternatives. Borda insisted that the best rule would instead make use of all the information contained in each individual's ranking of the options. His proposal amounts to selecting the alternative for which the sum of the assigned ranks is smallest.

Potential answers to the social welfare question necessarily depend on the types of information concerning preferences the planner deems meaningful. In particular, most of modern economic theory treats utility as identified only up to an individual-specific monotonic transformation, which precludes cardinal interpersonal comparisons.[1] Arrow's canonical formulation of the social welfare problem (Arrow, 1950) therefore assumes that the planner can only use ordinal information concerning preferences.[2] Invoking the aggregation axiom known as Independence of Irrelevant Alternatives (IIA) also effectively precludes the use of information on ranks.[3] The logic of IIA is traceable to Condorcet (Condorcet, 1788), who criticized the Borda rule on the grounds that it "relies on irrelevant factors to form its judgments," in that it "confuses votes comparing Peter and Paul with those comparing either Peter or Paul to Jack and uses them to judge the relative merits of Peter and Paul." While the Borda rule respects the modern proscription on using cardinal measures of well-being, it slips cardinality back into the social calculus through these types of third-option comparisons. Indeed, Borda' justification for the rule explicitly references cardinal inferences.[4]

Arrow's celebrated Impossibility Theorem (Arrow, 1950) precludes the existence of any rule for aggregating ordinal preferences satisfying IIA and certain other reasonable axioms. Yet groups cannot avoid preference aggregation merely because they might run afoul of a theoretical axiom. One way or another, they routinely make implicit or explicit judgments about tradeoffs between different members' objectives. Our overall goal in this paper is to understand those judgments.[5] In other words, we

[1]There is, however, a branch of the literature that attempts to justify such comparisons; see Roberts (2005) for a review.

[2]Arrow's assumption is "that interpersonal comparison of utilities has no meaning and ... that there is no meaning relevant to welfare comparisons in the measurability of individual utility" (Arrow, 1951).

[3]According to IIA, if a change in group members' preference rankings leaves the relative rankings of options A and B unchanged, then it also leaves social preferences between A and B unchanged.

[4]According to Borda (Borda, 1781), "...we must assume that the degree of superiority which this voter gave A over B is the same as that he gave B over C. As candidate B is no more likely to be ranked in one particular place on the scale between A and C than in any other, we have no reason to say that the voter who ranked the candidates ABC wanted to place B nearer A than C or vice versa; no reason to say, that is, that he accorded the first more superiority over the second than he accorded the second over the third."

[5]As in the literature on social welfare spawned by Arrow's work, we abstract from the important problem of eliciting accurate information about group members' preferences, which is the subject of a related literature; see, for example,

approach the classical social welfare question from a *positive* perspective rather than a *normative* perspective.[6] Illuminating fundamental attitudes toward ordinal preference aggregation is important because those attitudes have potentially profound implications for public policy. For example, by adopting institutions that tend to deliver desirable outcomes according to the Condorcet criterion, a society will become susceptible to what Mill, in *On Liberty*, termed the "tyranny of the majority" (Mill, 1869). In contrast, by embracing institutions that tend to deliver desirable outcomes according to the Borda rule, a society will provide greater protections for minority populations, whether associated with geography, ideology, ethnicity, or religion.

Our analysis addresses four main questions. First, what rules and criteria do people actually follow when aggregating ordinal preferences? For instance, do they impose compromise solutions, or insist that the majority should prevail? Second are these rules stable, or do they vary from one context to another? To what extent do they reflect structural principles of preference aggregation, rather than contextual adaptations? Third, do people honor ordinal information, or do they try to make cardinal imputations before aggregating? Fourth, do common aggregation rules vary across cultures with divergent political and social traditions, and might such variation help to explain differences in policies?

Identifying the rules that govern ordinal aggregation is conceptually challenging. Even in simple social choice problems (e.g., with five people and three options), the set of possible mappings from preference profiles to best choices is astronomically large. We therefore proceed in four steps. First, drawing on the theoretical literature, we identify a reasonably large set of plausible aggregation rules. Each of these rules implies a distinctive *fingerprint* of implied best choices over the set of conceivable five-person three-option preference profiles. Second, we conduct an experiment in which subjects in the role of Social Planner make a series of decisions for other groups of subjects (Stakeholders). We assign each subject to a pre-specified rule using a Bayes classifier, which identifies the best match between each subject's empirical fingerprint and the theoretical fingerprints associated with the various rules. Third, we corroborate the classifications using a handful of discerning four-option social choice problems. Fourth, we use a clustering algorithm to determine whether our pre-specified rules omit empirically important possibilities.

In order to elicit subject-level empirical fingerprints, each Social Planner makes decisions for multiple preference profiles, knowing that any one of them may involve a real group of Stakeholders who care about the outcome. The Social Planners' decisions are of two types: assignment decisions (distributing five work tasks among five Stakeholders), and spending decisions (assigning a contribution on behalf of five Stakeholders to a single Swiss political party). We call these the *work domain* and

Gibbard (1973) and Satterthwaite (1975). While issues of manipulability inevitably arise in practice, they pertain to the constraints that appear in a mechanism design problem, rather than to the objective function, and it is the latter we seek to illuminate. Notably, Borda was primarily concerned with the social welfare question, as he is said to have described his preferred rule as intended for honest men (quoted in Black, 1958).

[6] It is arguable that, in representative democracies, policy makers ought to defer to citizens' judgments about appropriate criteria for preference aggregation. Under that view, positive analyses of social choice have important normative implications.

the *political domain*, respectively. Most of our analysis focuses on the work domain; we examine the political domain to evaluate context-sensitivity. Because we are interested in identifying structural aggregation preferences, we design the experiment to remove considerations arising from self-interest, paternalism (i.e., the tendency to ignore or discount Stakeholder judgments with which the Social Planner disagrees, as in Ambuehl et al., 2021a), and the potential incentive incompatibility of truthful preference revelation by Stakeholders.

In answer to the first question (which rules do people use), we find that the overwhelming majority of subjects behave as if they rely on *scoring rules*, which assign a score to each rank and select best options based on the total scores.[7] The two most common as-if aggregation criteria are the Borda rule (for which the score is linear in ranks), and *near-antipluralilty* (where antiplurality rule minimizes the number of last-place ranks).[8] A sizable majority ($> 60\%$) of subjects employ *strictly concave scoring rules*, of which antiplurality is an example. Substantively, these rules imply an even stronger preference for compromise than the Borda rule; technically, they have the property that improvements in low ranks are more important than improvements in high ranks. Condorcet (majoritarian) rules are relatively rare, as is the related concept of plurality rule, and likewise associated runoff criteria. Neither do people often gravitate toward supermajority or unanimity (Pareto) rules, even though those also provide minorities with varying degrees of protection. The classification's fit is excellent: empirical and theoretical fingerprints for assigned rules are remarkably similar. Analysis of discerning four-option profiles corroborates our conclusions concerning the prevalence of various rules. Clustering analysis identifies only one non-pre-specified rule of consequence ($> 2\%$ of subjects), and it differs from near-antiplurality on only one of 17 preference profiles.

In answer to the second question (stable structure versus contextual adaptations), we find that our classifications are highly predictive of choices out of sample, including across domains. This result reassures us that ordinal aggregation entails stable structural elements. This is not to say that the distribution of rules is the same in the work domain and the political domain. On the contrary, the differences between these distributions, though relatively small, are systematic and statistically significant, which points to a degree of context-specificity.

In answer to the third question, we find strong indications that subjects aggregate ordinal preferences based in part on inferences about cardinal utility. As a threshold matter, it is worth emphasizing that scoring rules provide latitude for injecting cardinal inferences into the social choice, whereas the Condorcet rule does not. We explore this question in two ways. First, we provide evidence on the validity of a choice axiom known as *Sen's* α, which states that the removal of an unchosen option from an opportunity set should not alter the selection from that set. We demonstrate that choices satisfy

[7] Consistent with this finding, Featherstone (2019) shows that, in the context of matching markets, policymakers often evaluate matches based on rank distributions (a special case of scoring rules), and sometimes tinker with the results of matching algorithms in attempts to improve the rank-distribution.

[8] Antiplurality is the scoring rule that assigns 0 to the last-place rank and 1 to all other ranks. It is thematically related to (but substantively distinct from) *last place aversion*, which has been found in some experiments (Kuziemko et al., 2014; Martinangeli and Windsteiger, 2020) but not others (Camerer et al., 2016).

Sen's α when the preference rankings provided to the Social Planner include the deleted item, but severely violate Sen's α when we also remove the item from the rankings. We infer that subjects likely draw inferences about the intensity of preferences from comparisons with options that are generally considered undesirable. Second, we examine the correlation between best-fit scoring parameters and the scoring parameters our Social Planners would use if they were money-metric utilitarians, given their elicited beliefs about Stakeholders' reservation valuations for first-, second-, and third-ranked choices. While the correlation corroborates the importance of cardinal inferences, further investigation suggests that subjects attach substantial domain-independent weight to the various ordinal ranks. In other words, they appear to deploy both cardinal and ordinal criteria.

To answer to the fourth question (comparisons across countries), we run supplemental experiments using general population samples, wherein social choices determine the allocation of a contribution over well-known charities. We find that the distributions of aggregation preferences in the U.S. and Sweden, countries with divergent political and social traditions, are remarkably similar, and both resemble the distribution for the student sample used in our main experiment.[9] Policy differences may therefore be attributable to other factors, such as beliefs, historical accidents, institutions, and/or equilibrium selection, as hypothesized by Alesina and Angeletos (2005). Nevertheless, we find suggestive evidence that the use of more concave scoring rules in experimental decisions correlates with a preference for electing compromise candidates.

Most broadly, our paper contributes to the literature on *positive welfare economics*, which uses empirical methods to determine how people evaluate the well-being of other individuals and groups (e.g. Andreoni et al. (2020); Almås et al. (2020); Ambuehl et al. (2021a); see Konow (2003); Gaertner (2009); Gaertner and Schokkaert (2012) for reviews). To our knowledge, only a handful of previous papers in this area have attempted to address the problem of ordinal preference aggregation from a positive perspective. The most closely related paper is Kara and Sertel (2005). Their analysis is confined to three rules (Condorcet, Borda, and "majoritarian compromise"), which they distinguish based on a few (four) preference profiles using hypothetical choices involving abstract options. In contrast, we examine real choices, use far more exhaustive lists of rules and preference profiles, estimate scoring parameters, use clustering analysis to detect omitted rules, test out-of-sample predictive accuracy, examine stability across domains and cultures,[10] investigate whether subjects try to make cardinal inferences, and provide evidence of external validity using general population samples.

Other positive work on ordinal preference aggregation addresses different questions than ours. The analysis in Weber (2017), which focuses on two-option choices, seeks to determine how subjects weigh the votes of delegates who represent groups of different sizes in assemblies such as the EU. Other related work elicits subjects' preferences over (five or fewer) voting procedures, rather than

[9] Ambuehl et al. (2021b) include an abridged version of the current experiment in a study of elected representatives in federal and state parliaments in Germany. They find similar qualitative results.

[10] Faravelli (2007) documents the importance of context in social decisions.

over outcomes (Engelmann and Grüner, 2017; Hoffmann and Renes, 2017; Engelmann et al., 2020).[11] In these experiments, it is up to the subjects to imagine what each rule might imply for any particular preference profile. Those inferences are often non-trivial, and it is possible that a subject would reject a seemingly appealing rule after learning what it implies.[12] In contrast, our subjects reveal their preferences over rules by making choices over explicit social outcomes. Choices over procedures rather than social outcomes may also implicate strategic considerations or procedural notions of justice and equity, which we intentionally remove from our study in order to address the classical problem of ordinal preference aggregation.

Our work is also related to the vast empirical literature on *other-regarding preferences*, which generally studies preference aggregation in settings where cardinal information (typically concerning money) is available (see, e.g., Fehr and Fischbacher, 2002; Cooper and Kagel, 2016, for reviews). The most closely related branch elicits preferences over the distribution of income (e.g. Epper et al., 2020; Fisman et al., 2021). Most of this literature is concerned with self-versus-other tradeoffs, rather than other-versus-other tradeoffs, although there are some exceptions. For example, Jackson and Yariv (2014) examine how subjects in the role of a Social Planner aggregate others' cardinal preferences intertemporally in settings where rates of discount differ. An alternative to the self-versus-other and other-versus-other paradigms examines social choice behind a veil of ignorance, as in Engelmann and Strobel (2004). Those experimental settings tend to induce utilitarian decisions (Bolton and Ockenfels, 2006; Jackson and Yariv, 2014).

This paper draws heavily on, and complements, the theoretical social welfare literature (Arrow et al., eds, 1991, 2010; Fishburn, 2015; Brandt et al., 2016). Most obviously, it documents the empirical relevance of various rules, but there are other points of contact. By examining the tendency for people to make cardinal inferences from ordinal information about preferences, we provide empirical context for a theoretical literature on utilitarian-optimal voting rules (de Laplace, 1812; Weber, 1978; Merrill III, 1984; Apesteguia et al., 2011; Boutilier et al., 2015; Pivato, 2016).[13] Moreover, the low prevalence of Condorcet rules suggests that most people do not accept Condorcet efficiency (the frequency with which a rule selects the Condorcet winner when one exists) as a normative principle, contrary to the position of Merrill III (1984) and others; see, for instance, Van Newenhizen (1992); Saari (2000); Baharad and Nitzan (2003).

The remainder of the paper is organized as follows. We lay out our main strategy for detecting the use of specific social choice rules in Section 2. Section 3 details our experimental design. Section 4

[11] Another potential approach, which has been used in decision theory, is to ask subjects to endorse axioms rather than rules; see, e.g., Nielsen and Rehbeck (2020). Unfortunately, Arrow's theorem alerts us to the possibility that people might well endorse inconsistent axioms. In addition, social choice axioms are often complex and difficult for non-specialists to understand, and some common rules lack axiomatizations.

[12] Laslier (2012) reports the result of an informal vote by 22 voting theory experts on an ad hoc list of 18 aggregation rules. The winner is approval voting, followed by instant runoff. That vote considers rules comprehensively whereas this paper abstracts from strategic considerations to focus on the welfare (aggregation) question.

[13] Our conclusions concerning the tendency to infer cardinal values from ranks resonate with findings from a bargaining experiment by Herreiner and Puppe (2010), in which subjects received ordinal information concerning each others' preferences.

provides our classification results and all associated analyses. Section 5 describes our supplementary experiments involving general population samples. Section 6 provides some brief concluding remarks.

2 Conceptual framework

We are concerned with settings in which a decision maker, the *Social Planner*, must make a selection from a set of K social options, $\mathcal{A}$, on behalf of N *Stakeholders*. Each option has direct consequences for the Stakeholders, but the Social Planner is not materially affected by her decision. We assume throughout that each Stakeholder i has a linear preference ordering $\succsim_i$ over $\mathcal{A}$. To avoid technicalities we assume the orderings are strict (a property that is, in any case, generic). Before making a decision, the Social Planner learns the group's *preference profile*, $P = (\succsim_1, \ldots, \succsim_N)$. A *social choice rule* is a complete account of the Social Planner's choices for every preference profile; in other words, it is a mapping R from preference profiles into nonempty subsets of $\mathcal{A}$ (*best choices*).[14] A *resolute* rule admits no ties, in the sense that it maps every profile to single option. A rule is *irresolute* if at least one preference profile maps to a non-singleton set, indicating that there is more than one best choice.

Our objective is to determine which social choice rules people actually use when making decisions for others. The task of identifying these rules is challenging because the set of possibilities is astronomically large. To illustrate, consider a simple setting with 5 Stakeholders, where the Social Planner must choose among 3 options. In that case, the domain of any social choice rule satisfying *anonymity* (meaning that the rule treats all group members symmetrically) and *neutrality* (meaning that the rule treats all social options symmetrically) consists of 42 distinct preference profiles.[15] A social choice rule maps each of these profiles to a subset of the three options. Because there are seven such subsets, there are $7^{42} = 3.1 \times 10^{35}$ possible social choice rules for this simple environment. While most are unreasonable, 3.5×10^{28} exhibit no Pareto violations.[16]

Because the set of potential social choice rules is so large, our analysis proceeds in three steps. First, based on the literature, we identify a reasonably large collection of social choice rules encompassing the most plausible alternatives. Second, we classify Social Planners according to the pre-specified rules that most closely match their actual choices. Third, we deploy clustering analysis to determine whether our pre-specified rules omit empirically important alternatives.

[14] Arrow (1950) studied *social choice functions*, which map preference profiles into rankings over social alternatives. When A is finite, any social choice function F implies a corresponding social choice rule, which picks maximal elements according to F.

[15] We identified these profiles using an algorithm that enumerated all the alternatives and then eliminated ones that are redundant under anonymity and neutrality. It is also possible to arrive at the number of such profiles through a combinatorial argument. According to *The Hitchhiker's Guide to the Galaxy* by Douglas Adams, the number 42 is "The Answer to the Ultimate Question of Life, the Universe, and Everything," calculated by a supercomputer over 7.5 million year, but unfortunately no one knows the question. We are delighted to have resolved that mystery. You're welcome.

[16] The Pareto criterion rules out nothing for 27 profiles, one option for 12 profiles, and two options for 3 profiles. The number of rules without Pareto violations is therefore $7^{27} \times 3^{12}$.

In the remainder of this section, we summarize various social choice rules that our subjects may employ, and explain conceptually how we distinguish among them.

2.1 Possible social choice rules

There are in principle many ways to categorize social choice rules. For our purposes, the most useful classification references the nature of the information the rule employs. The reason is that, in designing an experiment such as ours, one must be alert to the possibility that the method of presenting information concerning the preference profile P may nudge the Social Planner toward one type of social choice rule or another. Understanding the information requirements for various classes of rules helps ensure a neutral presentation.

As an example, consider the *Borda method*, which selects options that minimize the sum of ranks across all Stakeholders. To implement this rule, one must know, for each $A \in \mathcal{A}$ and $k \in \{1, ..., K\}$, the number of group members who rank option A k-th among the potential alternatives, denoted r_A^k. We call this distillation of P the *Borda data*.

An important class of social choice rules known as *scoring rules* use only the Borda data. A scoring rule establishes a *score vector*, $w = (w_1, w_2, \ldots, w_K)$ with $w_1 \geq \ldots \geq w_K$, and allocates w_1 points to each Stakeholder's top-ranked alternative, w_2 points to their second-ranked alternative, and so on. It then selects an option that maximizes the sum of the scores.[17] Taking $w_k = k$ for all k yields the Borda rule. *Plurality rule* emerges as a special case: when $w_1 > 0$ and $w_k = 0$ for $k > 1$, the scoring method maximizes first-place ranks. Alternatively, taking $w_k = w_1 > 0$ for $k < K$ and $w_K = 0$, the scoring method minimizes last-place ranks, a rule known as *negative voting* or *antiplurality*.

As a second example, consider the *Condorcet method*, also known as *pairwise majority rule*, which selects an option that majority-defeats all others (a *Condorcet winner*). To implement this rule, one must know, for each pair of options, $A, B \in \mathcal{A}$, the number of group members who rank A strictly above B, denoted v_{AB}. We call this distillation of P the *Condorcet data*.

The Condorcet method is a special case of a *p-supermajority* rule, which declares option A better than option B if the fraction of Stakeholders who prefer A to B is at least p. The rule selects an option if it is not improvable according to this binary relation. Condorcet corresponds to the case in which p is the strict majority threshold, *Unanimity rule* (also know as the *Pareto rule*) to the case of $p = 1$, and *Supermajority rule* to intermediate cases. All p-supermajority rules use only the Condorcet data.

A well-known limitation of the Condorcet method is that it can give rise to cycles, and consequently does not yield a winner for certain preference profiles. The same issue arises for Supermajority rule, but not for Unanimity rule. To apply Condorcet (or Supermajority) on an unrestricted domain, one must supplement the rule. A *Condorcet extension* selects a Condorcet winner when one exists, but

[17] Myerson (1995) provides an axiomatic characterization of the set of scoring rules.

otherwise employs some other criterion.[18] An example is the *top cycle* or *Smith set*, defined as the smallest collection of options that majority-defeat all options in the complement of the set. Many Condorcet extensions use only the Condorcet data. Examples include the top cycle, the *Minimax method*, *Copeland's rule*, the *Kemeny-Young method*, *Tideman's rule*, and the *Schulze method*.

Having distinguished between classes of rules according to information they employ, it is important to emphasize that the Borda data are not in general recoverable from the Condorcet data, and the Condorcet data are not in general recoverable from the Borda data. Accordingly, a presentation of preference profiles that makes either type of information more salient could potentially skew choices accordingly.

Some social choice rules require more complete information concerning preference profiles. For example, *Black's method* is the Condorcet extension that selects the Borda winner when a Condorcet winner fails to exist. It therefore relies on both the Condorcet data and the Borda data. However, that reliance is hierarchical, in the sense that the Condorcet data take precedence.

Multistage rules that winnow down the set of alternatives in a series of steps introduce almost limitless possibilities, inasmuch as they can, in principle, apply different criteria in each step. Even when the rule employs the same criterion round after round, the required information evolves. Consider, for example, the set of *runoff rules* based on scoring criteria, which repeatedly eliminate the alternative with the lowest score until only one option remains.[19] A well-known example is the *single transferrable vote rule*, which iteratively deletes options with the lowest plurality scores. Another is *Baldwin's rule*, which uses the Borda score. Such rules employ the Borda data for a sequence of shrinking menus. That information is not recoverable from the Borda data for the original menu. Still, a presentation that highlights the Borda data may encourage the use of such methods.

2.2 Main identification strategy

The core of our empirical analysis differentiates among social choice rules based on selections for problems involving 5 Stakeholders and 3 options. This focus offers three advantages.

First, 5-Stakeholder 3-option problems are the simplest settings that provide adequate scope for differentiation among a broad collection of rules. While the addition of Stakeholders or options can in principle permit greater discernment, it can also render social choice problems less cognitively manageable.

Second, with K options, the set of scoring rules is a $K-2$ parameter family. Consequently, when $K=3$, we can associate each scoring rule with a single parameter, s. To understand this point, note that without loss of generality, we can assign a score of 1 to a Stakeholder's highest-ranked alternative, and a score of 0 to her lowest-ranked alternative. The parameter $s \in [0,1]$ is then the score assigned

[18]See Definition 2.8 in Brandt et al. (2016). The Campbell-Kelly theorem characterizes the set of Condorcet extensions (Theorem 2.3 in Brandt et al., 2016).

[19]For formal definitions and an axiomatic characterization, see Freeman et al. (2014).

to the middle alternative. The cases of $s = 0$, $s = 1/2$, and $s = 1$ correspond to the Plurality, Borda, and Negative Voting rules, respectively. The one-dimensionality of this class facilitates the interpretation of our results. In particular, the function relating ranks to weights is concave when $s > 1/2$, and convex when $s < 1/2$. Concavity (convexity) implies that replacing a third-place rank with a second-place rank is more (less) valuable than replacing a second-place rank with a first-place rank. Accordingly, concave scoring rules codify an aversion to giving Stakeholders their least favorite choices, while convex scoring rules codify an attraction to giving Stakeholders their favorite choices. These observations suggest that scoring rules may reflect inferences about cardinal utility,[20] a point to which we return in Section 4.6. They also suggest the interpretation of concavity as appreciation of compromise.

Third, with 5 Stakeholders and 3 options, we can in principle investigate choices exhaustively on the entire preference domain. As noted above, for social choice rules satisfying neutrality and anonymity, there are 42 distinct strict preference profiles. Eliciting a choice for every conceivable profile is therefore feasible.

In practice, many of the 42 preference profiles provide little or no discernment among rules. For example, if all Stakeholders have the same ranking, the best social choice is obvious. Including such problems lengthens the experiment, thereby risking the erosion of subjects' effort and attention, without adding significant value. Accordingly, we omit profiles that provide little or no differentiation among well-known rules. Our analysis is based on the 17 discerning profiles listed in Table 1. In Appendix A.1, we list the omitted profiles and exhibit their limited ability to distinguish among rules.

Table 1 also shows how the 17 profiles differentiate among familiar social choice rules. For example, if a subject uses a scoring rule, we can determine the parameter s from the choices they make for profiles 1 through 11. To understand this point, first consider profile 11. Because all subjects rank option B second, its score is $S_s(B) = 5s$. Four subjects rank option C first and one ranks it third, so its score is $S_s(C) = 4$. Option A is rank-dominated by C, so no scoring rule will select it. Therefore, the subject will choose option B if $S_s(B) > S_s(C)$, or equivalently, $s > 0.8$, and will choose option C if $s < 0.8$. If $s = 0.8$, the subject is indifferent between options B and C. Now consider profile 6, which differs from profile 11 only in that Stakeholder 2's preferences between A and C are reversed. Reasoning as before, we see that scoring rules select B over C when $s > 0.6$.

Profiles 1 through 11 constitute the set of all profiles for which there are exactly two options that are not weakly rank-dominated. For each, there is a threshold $\bar{s}$ at which the optimal choice switches, as in the cases of profiles 6 and 11. These thresholds divide the interval $[0, 1]$ into a sequence of subintervals with boundaries in the set $\mathcal{C} = \{0, \frac{1}{3}, \frac{1}{2}, \frac{3}{5}, \frac{2}{3}, \frac{3}{4}, \frac{4}{5}, 1\}$. Based on decisions for profiles 1-11,

[20] Apesteguia et al. (2011) formalize this point.

Table 1: Three-alternative profiles.

Index	Profile	Rule predictions										
		Scoring cutoff	Scoring rules. $s \in$					Condorcet	Runoff rules, $s \in$			
		$\bar{s}$	$\{0\}$	$(0, \bar{s})$	$\{\bar{s}\}$	$(\bar{s}, 1)$	$\{1\}$		$[0, \frac{1}{3}]$	$(\frac{1}{3}, \frac{1}{2})$	$(\frac{1}{2}, 1)$	$\{1\}$
1*	A A C C C B B A A A C C B B B	1/3	C	C	{A,C}	A	A	C	C	C	C	{A,C}
2	A C C B B B A A A A C B B C C	1/3	{B,C}	B	{A,B}	A	A	A	B	A	A	{A,B}
3*	A A A C C B C C B B C B B A A	1/2	A	A	{A,C}	C	C	A	A	A	A	{A,C}
4*	A A B B B B C A A A C B C C C	1/2	B	B	{A,B}	A	A	B	B	B	B	{A,B}
5	A C C C B B B B B A C A A A C	1/2	C	C	{B,C}	B	B	C	C	C	C	{B,C}
6*	A A C C C B B B B B C C A A A	3/5	C	C	{B,C}	B	B	C	C	C	C	{B,C}
7	A C C C B B A B B A C B A A C	2/3	C	C	{B,C}	B	B	C	C	C	C	{A,B}
8*	A C C C B B B B B C C A A A A	2/3	C	C	{B,C}	B	B	C	C	C	C	{B,C}
9*	A A A B B B C C C C C B B A A	3/4	A	A	{A,C}	C	C	A	A	A	A	{A,C}
10	A C C C C B A A A A C B B B B	3/4	C	C	{A,C}	A	A	C	C	C	C	{A,C}
11*	A C C C C B B B B B C A A A A	4/5	C	C	{B,C}	B	B	C	C	C	C	{B,C}
12	A C C B B B A A C C C B B A A	0	-	-	{B,C}	C	C	{A,B,C}	B	B	B	{A,C}
13	A C C B B B A A C A C B B A C	1/2	{B,C}	{B,C}	{A,B,C}	A	A	{A,B,C}	B	B	{A,B,C}	{A,B,C}
14	A C C B B B A B C C C B A A A	0	-	-	{B,C}	{B,C}	{B,C}	B	B	B	B	{B,C}
15	A C C B B B A B A A C B A C C	0	-	-	{B,C}	B	{A,B}	B	B	B	B	{A,B}
16	A C C B B B A B C A C B A A C	0	-	-	{B,C}	B	B	B	B	B	B	{A,B}
17	A C C B B B B B A A C A A C C	0	-	-	{B,C}	B	B	B	B	B	B	{A,B}

Notes: Each profile is displayed as a 3×5-matrix. Columns correspond to Stakeholders and rows to preference ranks. A Stakeholder's first, second, and third-ranked alternatives are listed in the first, second, and third rows, respectively. For Condorcet-cyclical profiles, we indicate the set of options in the top-cycle. For decisions in the political domain, we only use the profiles indicated with an asterisk.

we can determine which interval contains the subject's scoring parameter.[21] In some cases, we can also distinguish choices based on scoring parameters at the boundaries of these intervals.[22]

As shown in Table 1, the remaining profiles provide further scope for differentiating among social choice rules. For example, because profiles 12 and 13 exhibit Condorcet cycles, all three options are best choices according to the top-cycle Condorcet extension, but not according to many other rules.

Each social choice rule generates an identifiable "fingerprint" of selections across the 17 preference profiles; see Figure 1. Each column in the figure represents a 5-Stakeholder 3-option preference profile, which we identify in the first panel. For example, the first column corresponds to the profile wherein two Stakeholders prefer A to B to C, while three prefer C to A to B. Each subsequent panel corresponds to a specified social choice rule; it shows the options that rule selects for each preference profile. Comparing the fingerprints across rules (panels) reveals both similarities and differences.

Our main classification results encompass 22 benevolent social choice rules.[23] We start with the 15 distinguishable rules that emerge from the scoring method. We can differentiate between $s = \frac{1}{2}$ (the Borda rule), 5 ranges of scoring parameters in the convex range (the most extreme of which corresponds to Plurality rule), and 10 ranges of strictly concave rules (the most extreme of which corresponds to Antiplurality rule). Our data can also differentiate among 4 social choice rules that emerge from the scoring runoff method. These rules correspond to values of s in the following ranges: $[0, \frac{1}{3}]$, $(\frac{1}{3}, \frac{1}{2})$, and $[\frac{1}{2}, 1)$, as well as $s = 1$.[24] Finally, we can distinguish three social choice rules that emerge from the p-supermajority top-cycle method. These rules correspond to values of p in the following ranges: $[\frac{1}{2}, \frac{3}{5}]$, $(\frac{3}{5}, \frac{4}{5}]$, and $(\frac{4}{5}, 1]$. Henceforth we adopt a slight abuse of terminology and call these rules Condorcet, Supermajority, and Unanimity, respectively. While our basic classification does not include other Condorect extensions, we conduct robustness analyses to determine whether this omission is material.

Because we distinguish between social choice rules based on their fingerprints, larger differences between fingerprints facilitate more reliable classifications. Figure 2 tabulates, for each pair of social choice rules, the number of preference profiles (out of the 17 we use for identification) for which their implications differ. Two patterns stand out. First, in the vast majority of cases, different rules have different implications for large numbers of profiles. Ignoring the diagonal, few of the entries in Panel A are less than 3, and many are greater than 8, indicating differences on more than half of profiles.

[21] As indicated in Table 1, profile 13 provides corroborative evidence as to whether $s \lesseqgtr \frac{1}{2}$, and the remaining profiles shed light on whether $s = 0$.

[22] When a scoring parameter coincides with an interval boundary $s \in \mathcal{C}$, the set of options selected for a given preference profile is the union of those selected with scoring parameter $s - \epsilon$ and those selected with scoring parameter $s + \epsilon$ for $\epsilon > 0$ sufficiently small. Accordingly, scoring rules with parameters $s \in \mathcal{C}$ are less resolute (produce more ties) than scoring rules with parameter $s \notin \mathcal{C}$.

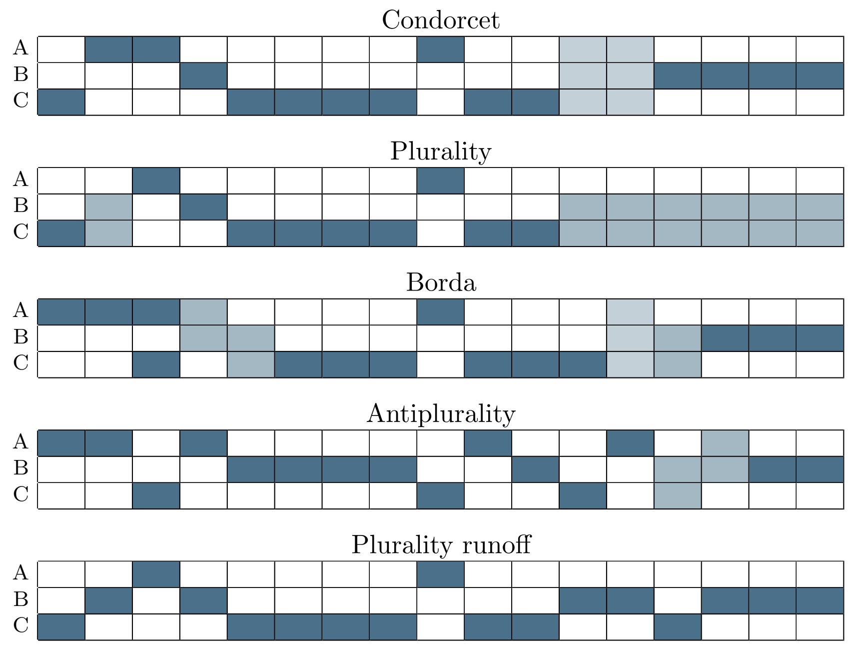
[23] We define a rule as *benevolent* if it satisfies the Pareto criterion.

[24] We implement scoring runoff rules as follows. In the first stage, we calculate the score associated with each option and drop the option with the lowest score. We then choose the majority-preferred option from the remaining alternatives. (Because this step involves at most two options, majority rules coincides with all scoring rules.) If two options are tied, we drop both of them. If all three options are tied, the runoff rule selects all of them. Three-way ties occur only for profile 13, and only for scoring runoff rules with $s \geq \frac{1}{2}$. We identify the set of distinguishable scoring runoff rules using a brute-force computer script.

Figure 1: Fingerprints of an example selection of social choice rules.

Preference profile

Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
$A > B > C$	2	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1
$A > C > B$	0	0	2	1	0	0	0	0	2	0	0	0	0	0	0	0	0
$C > A > B$	3	2	0	0	0	0	1	0	0	4	0	2	2	1	1	1	0
$C > B > A$	0	0	2	0	3	3	2	3	0	0	4	0	0	1	1	1	2
$B > C > A$	0	0	0	0	0	0	0	1	2	0	0	2	1	2	0	1	0
$B > A > C$	0	2	0	3	1	0	1	0	0	0	0	0	1	0	2	1	2



Notes: Each column corresponds to a three-alternative preference profile. Preference profiles are listed in the top row. The number in each cell in the top row indicates the number of Workers with the indicated preference ranking. Cells in the top row indicate the number of subjects with each of the preference orderings listed on the left of that row. Each cell in rows 2 to 5 is labeled 1 if the rule chooses the corresponding option and 0 if the rule does not choose the option. Non-resolute rules will choose more than one option for some profiles. Shades of blue indicate the number of tied options. The numbering of preference profiles corresponds to Table 1.

Second, three clusters of similar rules are visible. The first cluster consists of the strictly convex scoring rules numbered 2 to 4. The second cluster corresponds to the strictly concave scoring rules, numbered 6 to 15 (especially 6 to 8 and 12 to 15). Because these rules are members of the single family that is indexed by a continuous parameter s, adjacent rules tend to differ on small numbers of profiles, but more distant scoring rules are more easily differentiated. The third cluster consists of the scoring runoff rules with $s < 1$ (numbered 16 to 18). Observe also that the runoff rules, as well as the Condorcet rule (number 20), align more closely with convex scoring rules than with concave scoring rules. Hence, a preference for compromise may push subjects away from scoring runoff rules.

Figure 2: Distance between rules.

	Scoring, $s=0$	Scoring, $0<s<\frac{1}{3}$	Scoring, $s=\frac{1}{3}$	Scoring, $\frac{1}{3}<s<\frac{1}{2}$	Scoring, $s=\frac{1}{2}$	Scoring, $\frac{1}{2}<s<\frac{3}{5}$	Scoring, $s=\frac{3}{5}$	Scoring, $\frac{3}{5}<s<\frac{2}{3}$	Scoring, $s=\frac{2}{3}$	Scoring, $\frac{2}{3}<s<\frac{3}{4}$	Scoring, $s=\frac{3}{4}$	Scoring, $\frac{3}{4}<s<\frac{4}{5}$	Scoring, $s=\frac{4}{5}$	Scoring, $\frac{4}{5}<s<1$	Scoring, $s=1$	Runoff, $0\leq s\leq\frac{1}{3}$	Runoff, $\frac{1}{3}<s<\frac{1}{2}$	Runoff, $\frac{1}{2}<s<1$	Runoff, $s=1$	Condorcet	Supermajority	Unanimity
Scoring, $s=0$	0	5	6	6	10	10	11	11	13	13	15	15	16	16	16	7	7	7	16	7	15	17
Scoring, $0<s<\frac{1}{3}$	5	0	2	2	6	6	7	7	9	9	11	11	12	12	13	3	4	4	16	4	15	17
Scoring, $s=\frac{1}{3}$	6	2	0	2	6	6	7	7	9	9	11	11	12	12	13	5	5	5	14	5	15	16
Scoring, $\frac{1}{3}<s<\frac{1}{2}$	6	2	2	0	4	4	5	5	7	7	9	9	10	10	11	5	4	4	16	4	15	17
Scoring, $s=\frac{1}{2}$	10	6	6	4	0	4	5	5	7	7	9	9	10	10	11	8	7	6	12	6	14	15
Scoring, $\frac{1}{2}<s<\frac{3}{5}$	10	6	6	4	4	0	1	1	3	3	5	5	6	6	7	8	7	7	16	7	15	17
Scoring, $s=\frac{3}{5}$	11	7	7	5	5	1	0	1	3	3	5	5	6	6	7	9	8	8	15	8	15	17
Scoring, $\frac{3}{5}<s<\frac{2}{3}$	11	7	7	5	5	1	1	0	2	2	4	4	5	5	6	9	8	8	16	8	15	17
Scoring, $s=\frac{2}{3}$	13	9	9	7	7	3	3	2	0	2	4	4	5	5	6	11	10	10	15	10	15	17
Scoring, $\frac{2}{3}<s<\frac{3}{4}$	13	9	9	7	7	3	3	2	2	0	2	2	3	3	4	11	10	10	16	10	15	17
Scoring, $s=\frac{3}{4}$	15	11	11	9	9	5	5	4	4	2	0	2	3	3	4	13	12	12	14	12	16	16
Scoring, $\frac{3}{4}<s<\frac{4}{5}$	15	11	11	9	9	5	5	4	4	2	2	0	1	1	2	13	12	12	16	12	16	17
Scoring, $s=\frac{4}{5}$	16	12	12	10	10	6	6	5	5	3	3	1	0	1	2	14	13	13	15	13	17	17
Scoring, $\frac{4}{5}<s<1$	16	12	12	10	10	6	6	5	5	3	3	1	1	0	1	14	13	13	16	13	17	17
Scoring, $s=1$	16	13	13	11	11	7	7	6	6	4	4	2	2	1	0	15	14	14	15	14	17	17
Runoff, $0\leq s\leq\frac{1}{3}$	7	3	5	5	8	8	9	9	11	11	13	13	14	14	15	0	1	2	17	3	15	17
Runoff, $\frac{1}{3}<s<\frac{1}{2}$	7	4	5	4	7	7	8	8	10	10	12	12	13	13	14	1	0	1	17	2	15	17
Runoff, $\frac{1}{2}<s<1$	7	4	5	4	6	7	8	8	10	10	12	12	13	13	14	2	1	0	16	1	14	16
Runoff, $s=1$	16	16	14	16	12	16	15	16	15	16	14	16	15	16	15	17	17	16	0	16	16	13
Condorcet	7	4	5	4	6	7	8	8	10	10	12	12	13	13	14	3	2	1	16	0	13	15
Supermajority	15	15	15	15	14	15	15	15	15	15	16	16	17	17	17	15	15	14	16	13	0	4
Unanimity	17	17	16	17	15	17	17	17	17	17	16	17	17	17	17	17	17	16	13	15	4	0

Notes: This graph plots the set of 22 benevolent rules on both the horizontal and vertical axes. Each cell reports the number of profiles (out of the 17 used in the work domain) for which a given pair of rules differ from each other. We use the definition that two rules differ on a profile if they select a different subset of options (distance = 1); otherwise they do not differ on that profile (distance = 0).

3 Experimental design

3.1 Social choice problems

Overview We assign subjects to one of two roles: each *Social Planner* ('she') chooses alternatives that potentially affect groups of five *Stakeholders* ('he'). The only purpose of including Stakeholders in the experiment is to ensure that the Social Planners' decisions are consequential. Choice problems fall into two domains, task assignment (*work*) problems and budget allocation (*political*) problems. These domains relate, respectively, to mechanism design and political economy, two areas where ordinal preference aggregation is an important topic. For each domain, the Social Planner views a sequence of preference profiles and, in each instance, selects one of several alternatives. We match one out of every four Social Planners, selected at random, with a real group of Stakeholders. The actual preference profile for that group is among the ones that Social Planner considers, but is not identified as such. Although we only implement decisions that pertain to actual Stakeholder groups, from each Social Planner's perspective any one of her decisions could turn out to be a real choice.

Consequently, as long as she cares about the Stakeholders to some degree, she has an incentive to reveal her aggregation preferences truthfully for every preference profile she encounters. We focus primarily on the work domain, for which we employ the 17 profiles shown in Table 1. We examine the political domain, for which we employ a smaller set of profiles, to evaluate context-dependence.

Tasks for the work domain For the work domain, Stakeholders are *workers*, whom we recruit on Amazon Mechanical Turk. Each worker receives $15 for completing a single assigned task.[25] The compensation is sufficiently high to ensure that any attrition is non-systematic.

There are five work tasks. We choose tasks that resemble familiar activities for online workers, and that different workers might plausibly rank in different orders. The tasks are as follows: (i) *Image labeling.* The worker views a sequence of 400 images and identifies each by clicking a button. (ii) *Hate speech filtering.* The worker views 400 messages posted on twitter.com and indicates whether each includes hate speech such as racist or sexist statements. (iii) *Audio transcription.* The worker listens to a sequence of 400 words and, in each case, identifies the word by clicking a button. (iv) *Movie reviews classification.* The worker classifies 400 movie reviews according to whether they are positive or negative. (v) *Assigning apprentices to mentors.* The worker finds a pairwise stable match between five hypothetical apprentices and five hypothetical mentors knowing their preferences. The worker completes 20 rounds of this task.

Workers reveal their preferences over tasks in a preliminary session. After seeing a description of each task and trying it out to gain familiarity (except for the matching task, a single round of which some subjects find time-consuming), workers then rank the tasks from most to least preferred. We ensure incentive compatibility by informing workers that their rankings determine the task they perform with 5% probability, as follows: the computer randomly pre-selects two tasks, and workers perform the one they say they prefer. To preclude strategic reporting, we tell workers that some other process will determine their assigned tasks with 95% probability. Because we leave that process unspecified, workers have no information about the manner in which their own expressed preferences may factor into the alternative process. After the Social Planners make their choices, Workers complete their assigned tasks in a second session.

Social choice problems for the work domain A social alternative is a *task assignment*: it assigns each of the five tasks to one of the five workers in a group. Social Planners choose from menus of task assignments. For 3-option problems, menus consist of three randomly selected task assignments.

For the main portion of our experiment, Social Planners are students at the University of Zurich and the Swiss Federal Institute of Technology. (We examine US and Swedish general population samples in Section 5). At the beginning of the experiment, they acquaint themselves with the work tasks by reading descriptions and performing abbreviated versions (except for the matching task).

[25] Our survey automatically checks for correctness and requires the worker to continue until the entire task is completed correctly.

Their instructions describe the mTurk platform and provide information on the value of hourly worker compensation in our experiment.

A Social Planner proceeds through several rounds of decision making for her group. In each round, she observes an ordinal preference profile for the task assignments. One of these corresponds to her workers' actual preferences over task assignments, which we infer from their elicited preferences over tasks.[26] The Social Planner then chooses an assignment she considers best for the group. We also ask her to identify any alternative she considers just as good as the one she selects. While this expression of indifference has no consequences within our experiment, two considerations may mitigate the usual concerns about hypothetical choices: first, the question asks the Social Planner to report indifference that she presumably would have recognized when making the associated consequential choice moments prior; second, misrepresenting her indifference would not serve any other plausible objective (e.g., enhancement of social image).[27] However, as a precaution, we adopt two complementary approaches to identifying social choice rules, one of which uses the indifference data, and one which does not.

Recent research on paternalism shows that people tend to discount or even disregard preferences with which they disagree (Ambuehl et al., 2021a). That consideration is orthogonal to the focus of the current paper, which concerns the aggregation of ordinal preferences that are equally valid in the eyes of the Social Planner. To ensure that Social Planners cannot second-guess a worker's preferences (for example, by placing little weight on an expressed desire to complete the hate-speech filtering task), we limit the Social Planner's knowledge about task assignments. Specifically, we show the Social Planner a menu of abstract geometric symbols, explain that each represents a task assignment, and describe each worker's ranking of those assignments. However, we do not explain which worker performs which task in any given assignment.

In Section 2.1, we emphasized that different social choice rules use different data concerning preference orderings, and consequently that the presentation of preference profiles can potentially nudge Social Planners in one direction or another by highlighting particular information. Because a preference profile is an array of three-tuples of the form (option, worker, rank) that indicate the preference rank a particular worker assigns to a given option, there are three qualitatively different ways to display it in a two-dimensional table: rows and columns can be ranks and workers (in which case options appear in cells), ranks and options (in which case workers appear in cells), or workers and options (in which case ranks appear in cells).

We show the first possibility in Figure 3, which represents each worker as a vertical bar. Within each bar, the geometric symbols representing the assignments are ordered according to the worker's

[26] This information captures the workers' selfish preferences over task assignments. Any social preferences workers may have over task assignments might be interdependent, in the sense that each worker may wish to take other workers' preferences into account. To avoid such issues, we leave all interpersonal judgments to the Social Planner.

[27] An alternative procedure would be to (partially) incentivize indifference statements by randomizing among the pertinent options. We decided against that approach for two reasons. First, the procedure changes the nature of social alternatives by introducing lotteries over assignments, and thereby implicating workers' preferences over lotteries. Second, the social choice rules we consider do not specify random resolution. Adding that provision to a rule amounts to creating a non-standard extension.

preference, with the most preferred assignment on top. By clicking buttons, Social Planners can highlight or hide options. Highlighting an option makes the distribution of its ranks (the Borda data) readily apparent. When an option is hidden, the display repositions the remaining assignments onto two lines. This feature makes pairwise preference counts (the Condorcet data) readily apparent. Additionally, Social Planners can hide or rearrange the workers, either by dragging and dropping them, or by clicking a button to shuffle them randomly.

We show the second and third possibilities in Figures 4 and 5, respectively. With these presentations, the Borda data are arguably more salient, but Social Planners can easily access the Condorcet data by hiding options one at a time. Accordingly, we provide the same tools for exploration (hiding, highlighting, and rearranging).

Each Social Planner sees one and only one presentation format, which we select at random. We randomize symbols (representing options) and colors (representing workers) to ensure Social Planners do not conflate decisions across preference profiles.[28] We also randomize the positions of all alternatives and of all workers in each round.

In addition to the 17 preference profiles shown in Figure 1, each Social Planner who is matched to a real group of five workers views that group's actual preference profile and makes a choice, while other Social Planners view a randomly generated preference profile. Social Planners also make decisions for six four-option preference profiles and one two-option profile, which we randomly intermingle with the three-option profiles. Social Planners then view three final preference profiles, each of which rank either three or four alternatives, but they choose from menus that omit one of the alternatives. We provide more detail concerning all of these additional profiles and decisions in Sections 4.4 and 4.6. Altogether, Social Planners make choices for 28 preference profiles in the work domain.

The political domain To determine whether Social Planners apply consistent aggregation criteria across domains, we also present them with decisions involving political contributions. In this domain, Stakeholders (*citizens*) are voting-age members of the general Swiss population.[29] Social Planners, who are also voting-age Swiss nationals, direct a contribution of Fr. 30 (roughly \$33.90 at the time of the experiment) to one of the five largest Swiss political parties, as measured by the number of members in the Swiss National Council.

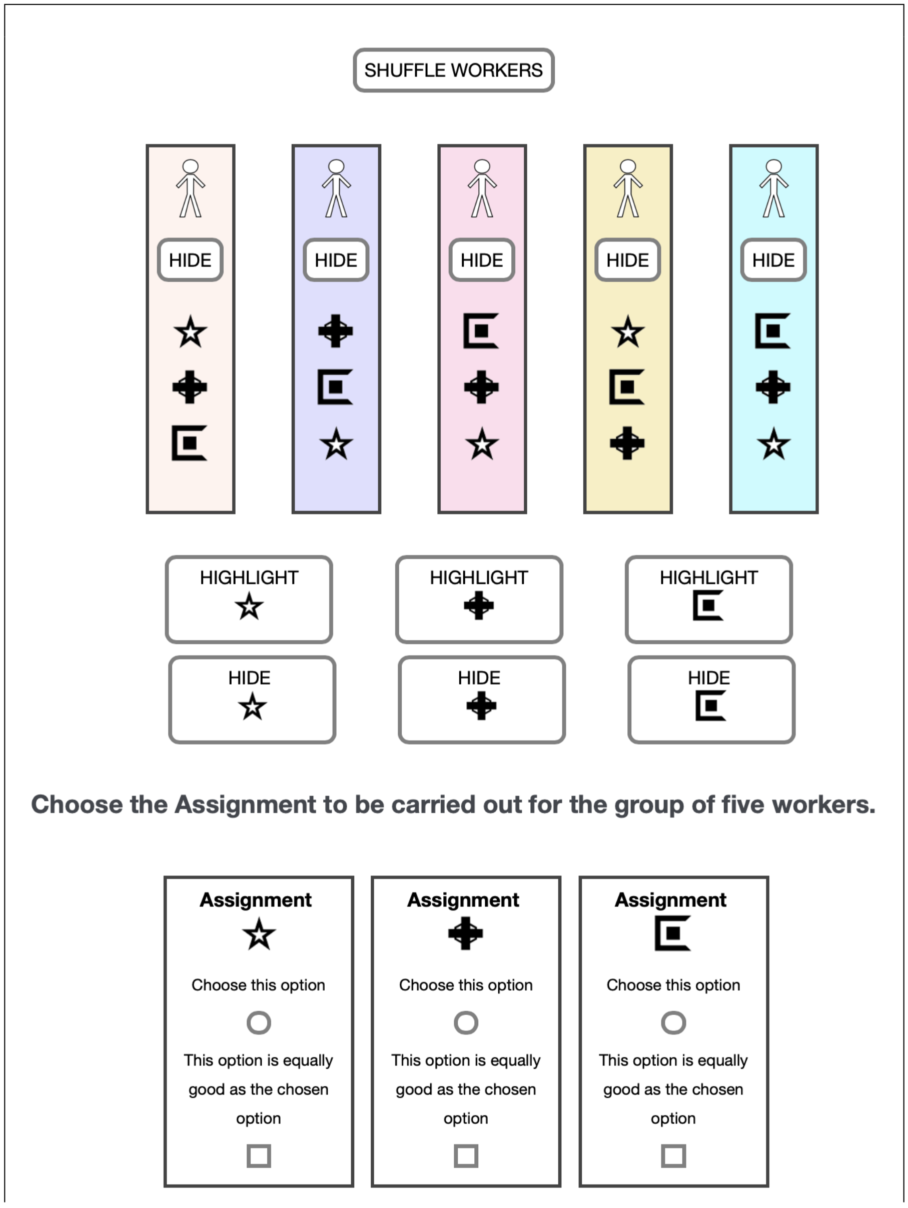
The procedures we use for political contributions are generally the same as for the work domain.[30] Here it is especially important to emphasize that, for any given preference profile, Social Planners

[28] For instance, this procedure prevents a Social Planner from deciding to favor the 'red worker' in one round because she disfavored that worker in the previous round.

[29] We recruited Stakeholders mostly through the survey company pollfish.com. We supplemented this sample by placing ads on Facebook and in the laboratory at the University of Zurich. Age and citizenship are self-reported.

[30] One exception involves the process for eliciting Stakeholders' preferences: citizens' expressed preferences determine the recipient of the donation with 2.5% probability, versus 5% probability for the analogous contingency in the work domain.

Figure 3: Social Planners' decision interface, version 1 (options in cells).

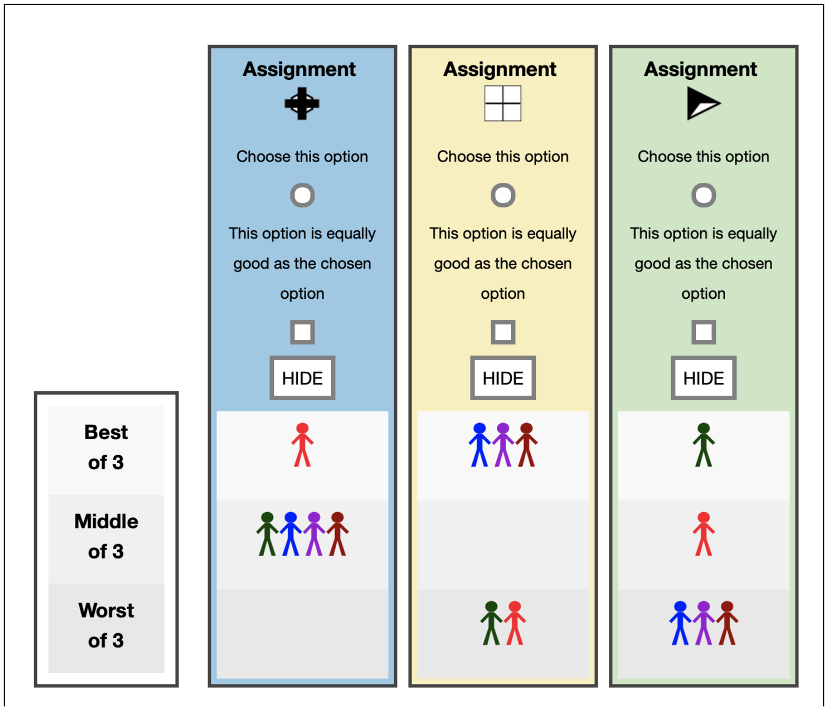


Notes: Subjects can drag and drop columns, click a button to shuffle columns, highlight choice options, hide choice options, and hide workers. If a subject hides an option, the remaining options are arranged on two rows regardless of their initial position. Symbols for options and colors for the bars representing each worker are randomly drawn each round. The order of workers is randomly drawn each round.

do not know which geometric symbol corresponds to which party, so they cannot impose their own political preferences.[31]

[31] To prevent Social Planners from drawing inferences about parties from preference distributions, we draw the group of five citizens from a sample that equally represents those who self-identify as politically left, right, and center. Social Planners are aware of the sample's composition.

Figure 4: Social Planners' decision interface, version 2 (individuals in cells)



Notes: Subjects can drag and drop columns, click a button to shuffle columns, hide choice options, highlight workers, and hide workers. If a subject hides an option, only two rows are shown; the remaining rows are labeled 'Best of 2' and 'Worst of 2.' Symbols for options and colors for worker symbols are randomly drawn each round. The order of options is randomly drawn each round.

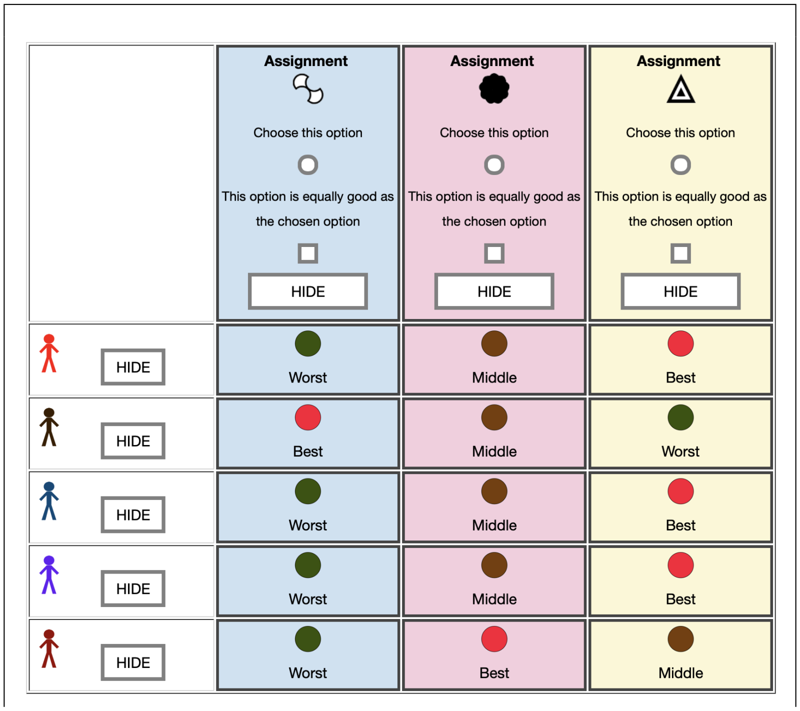
To keep the length of the experiment manageable for our subjects, we use a smaller set of preference profiles for the political domain. Over 12 rounds, Social Planners view, in random order, the starred preference profiles in Column 2 of Table 1, a selection of four four-option profiles (see Section 4.4), and one additional profile (either the actual profile for her assigned citizen group or a randomly generated profile, depending on whether we assign her to a group).

3.2 Additional elicitations

Beliefs about WTA / WTP For the work domain, we ask Social Planners to predict the average reservation wages for the tasks workers rank first, second, and third, knowing only that rankings involve three tasks randomly selected from the five possibilities.[32] To increase statistical power, Social Planners answer five (nearly) redundant versions of these questions, where each version specifies the

[32]Possible answers range from \$0 to \$10 in increments of \$0.50. Half of the subjects see these questions ordered by rank (first, second, third), and half see them ordered by reverse rank (third, second, first). Before subjects answer these questions, we remind them about the price and income level in the US and the standard wages of mTurk workers. The instructions for these tasks explain the concept of WTP using an example for which we randomize the elicited valuation (either \$5 or \$1).

Figure 5: Social Planners' decision interface, version 3 (ranks in cells)



Notes: Subjects can drag and drop columns, drag and drop rows, click a button to shuffle columns, click a button to shuffle rows, highlight preference ranks, hide choice options, and hide workers. If a subject hides an option, only two symbols, labeled 'best' and 'worst' are shown. The color of the symbols labeled 'best' and 'worst' differs depending on whether two or three options are displayed, to signify that the best (worst) option among two is not necessarily best (worst) among three. Symbols for options and colors for worker symbols are randomly drawn each round. The orders of workers and options are randomly drawn each round. Colors for the preference ranks are randomly drawn on the individual level but remain constant throughout the experiment.

city and state where the worker lives.[33] In the event one of these predictions ends up determining the Social Planner's payment, she receives Fr. 30 minus Fr. 3 for every dollar by which her prediction differs from the truth, which we assess using incentivized multiple decision lists in preliminary sessions involving a separate set of workers.[34]

For the political domain, we ask Social Planners to predict the average Swiss citizen's willingness to pay to trigger or prevent the donation workers rank first, second, and third. The details are the same as for the work domain, with a few small exceptions.[35]

[33] We use two sets of five city labels, randomly assigned, so we can determine whether the labels are consequential.

[34] Social Planners also indicate their own reservation price for completing each of the five tasks, but these responses are unincentivized.

[35] Possible predictions for the WTP to trigger the donation lie in the set {>15, 15, 13, 11, 9, 7, 5, 3, 1, -1, -3, -5 ,-7, -9, -11, -13, -15, <-15}. Over the five rounds, Social Planners make predictions for citizens with different first names rather than different cities of residence.

As we discuss subsequently, we use these responses to assess the hypothesis that Social Planners aggregate ordinal preferences based on implicit inferences about cardinal utility (as suggested in Apesteguia et al., 2011).

Risk preferences We elicit risk preferences using the method developed in Holt and Laury (2002). On each line of a multiple decision list, subjects choose between two lotteries. The first lottery pays Fr. 23 with probability p or Fr. 15 with probability $(1-p)$. The second pays Fr. 38 with probability p or Fr. 3 with probability $(1-p)$. The list includes 11 binary choices with $p \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$. In a second otherwise identical decision list, the first lottery pays either Fr. 20 or Fr. 13, while the second pays either Fr. 34 or Fr. 5.

Social preferences Subjects complete a multiple decision list involving the following pairs of alternatives: "*Increase each of the five workers' payoffs by \$2. Decrease my own study payment by CHF X*," or "*Do not increase the group members' payoffs. Leave my own study payment unchanged.*" Each line employs a different value of X in the set $\{0, 1, 2, 3, 4, 6, 8, 10, 12, 14, 16, 18, 20\}$. In an otherwise identical second list, the first option is *"Increase each of the five workers' payoffs by Fr. X (exchanged to USD). Decrease my own study payment by Fr.* $5X$," and the values of X lie in $\{0.2, 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2\}$. Notice that the first list implicates both efficiency and equity, while the second implicates only equity.

Psychological characteristics, knowledge of social choice theory, and demographics Subjects complete the four-item version of the Cognitive Reflection Test by Thomson and Oppenheimer (2016). For the last 143 subjects, we added four questions probing their knowledge of social choice theory.[36] Subjects also report a variety of personal characteristics.[37]

3.3 Additional details

Timing Table 2 provides an overview of the experiment's temporal structure. Social Planners perform ordinal preference aggregation tasks in parts A (work domain) and B (political domain). Within each domain, we display preference profiles in individually random order. We also randomize the order of Parts A and B, and include instructions about the decision interface in the part that appears first. To avoid nudging subjects to think about cardinal utility, we elicit risk aversion and beliefs about WTA/WTP in Part C, after the preference aggregation tasks are complete.

[36] Subjects report whether they have taken a class covering pertinent topics. We illustrate a three-option, three-citizen cyclical preference profile and ask subjects to name the paradox. We also ask subjects to name the Borda rule and Arrow's impossibility theorem based on verbal descriptions.

[37] These include: gender, age, field of study and degree level they are working towards, grades in university entrance exams in mathematics and in their first language, canton in which they completed their university entrance exam, their main language, whether they live with their parents, their number of siblings, monthly spending, religiosity, religion, political stance, and political party they voted for in the last election of the Swiss National Council.

Table 2: Schematic overview of the experiment.

Part 0: Initial instructions

Part A: Task assigment

1. Instructions concerning task assignment
2. Instructions about the interface that displays preference profiles
3. 25 task assignment decisions (intermingled)
4. 3 task assignment decisions with unavailable options (intermingled)

Part B: Donation to a political party

1. Instructions concerning the donation to a political party
2. 12 party donation decisions

Part C: Further elicitations

1. Beliefs
   - 5 rounds of incentivized belief elicitation about workers' reservation wages, followed by an unincentivized elicitation of own reservation wages for completing each of the five tasks
   - 6 rounds of incentivized belief elicitation about citizens' political preferences, followed by an unincentivized elicitation of own willingness to pay to trigger or prevent the donation to each of the political parties
2. Preferences
   - Risk preferences
   - Social preferences
3. Other characteristics
   - Demographic information
   - Cognitive Reflection Test
   - Knowledge about social choice theory

Notes: Each stage in Part C directly follows instructions concerning that stage. Half of the subjects proceed through the experiment in the order displayed. For the other half, Part B and Part A are interchanged. The latter subjects receive the instructions about the interface that displays preference profiles in Part B instead of in Part A. For those subjects, the two stages of Part C.1 are also interchanged.

Incentives A randomly selected decision (pertaining to WTP/WTA, risk preferences, or social preferences) from part C determines the Social Planner's own payment. As we have explained, social choices are incentivized in the sense that each one may be consequential for others, and we also incentivize the elicitation of workers' preferences.

Instructions and comprehension checks The full instructions for Social Planners, which we present on-screen, appear in Appendix E.1. The presentation requires subjects to try out each option in the preference display (e.g., hide and highlight). Subjects must pass two comprehension checks to continue with the study.[38] Each consists of nine questions. The first set concerns the preference displays and the second concerns the general decision environment. Subjects must answer all nine questions correctly to proceed. If they make a mistake, we ask them to review the instructions and try again, but we do not tell them which question(s) they missed.[39] We conduct the experiment English.[40]

4 Analysis

Our analysis focuses on 405 subjects in the role of Social Planner recruited from the joint subject pool of the University of Zurich and the Swiss Federal Institute of Technology. Subjects participated in 11 online sessions, supervised via video-conferencing software (Zoom), in January 2021. We restricted the sample to Swiss citizens by checking each participants' government-issued ID.

The median subject completed the session in 82 minutes and received Fr. 50.[41] In addition to the 405 subjects who completed the study, another 12 potentially eligible subjects started it.[42] Only five subjects failed to complete the experiment after presenting a valid ID. The implied attrition rate among potentially eligible subjects was therefore between 1.2% and 3%. The median age is 23. Among the subjects who were asked, 7% reported having taken a class that covered social choice theory, but only 1%, 3%, and 2% could correctly name Arrow's theorem, the Condorcet paradox, and the Borda rule, respectively. While our subject pool includes a higher proportion of women (61%) than men and skews towards the political left (70%, 15%, and 14% of subjects rate themselves as left, center, and right, respectively), Section 5 shows that similar results obtain in general population samples.

We structure our analysis as follows. Subsection 4.1 exhibits aggregate choice patterns. Subsection 4.2 presents our main classification results for the work domain. In Subsection 4.3, we use clustering methods to determine whether our classification omits any empirically important social choice rules. Subsection 4.4 provides corroborating evidence on classifications using discerning four-option profiles. Subsection 4.5 then investigates the extent to which our classification captures structural aggregation principles by comparing choices across domains and by evaluating out-of-sample predictive

[38] These are also listed in Appendix E.1.

[39] This feature prevents the subject from trying to pass the comprehension check by trial and error (the chance of passing either of the comprehension checks by chance is less than 0.2%).

[40] A good command of English is a curricular requirement for all students in our subject pool. The invitation emails mention that subjects must be fluent in English.

[41] At the time of the experiment, 1 Fr. = USD 1.13.

[42] An additional 7 subjects started the study but were not eligible.

performance. In Subsection 4.6, we investigate the extent to which aggregation rules reflect cardinal imputations. Throughout, we pool across the three methods of presenting preference profiles, but mention instances where results differ.

4.1 Aggregate choice patterns

Figure 6 shows choice frequencies for each of the 17 three-option profiles in the work domain. Structure is readily apparent, such as the near-unanimous decisions for profiles 2, 16, and 17. Because nearly all subjects choose the option that is both rank-dominant and a Condorcet winner in profiles 16 and 17, we can infer that they act benevolently toward their groups. Notably, disagreements are common for the score-identifying profiles 3 to 11, indicating heterogeneity in preferred aggregation criteria.

Figure 6: Distribution of choices in three-option problems

Profile	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Condorcet	C	A	A	B	C	C	C	C	A	C	C	ABC	ABC	B	B	B	B
Scoring																	
$\bar{s}$	$1/3$	$1/3$	$1/2$	$1/2$	$1/2$	$3/5$	$2/3$	$2/3$	$3/4$	$3/4$	$4/5$	-	$1/2$	0	0	0	0
$s < \bar{s}$	C	B[a)]	A	B	C	C	C	C	A	C	C	C[a)]	BC	-	-	-	-
$s > \bar{s}$	A	A	C	A	B	B	B	B	C	A	B	C	A	BC	B[b)]	B	B
Choice freq.																	
A	86	96	36	63	1	0	1	1	72	29	1	1	73	1	6	1	1
B	0	2	0	37	75	61	43	39	3	0	29	8	15	62	93	98	99
C	13	1	64	0	24	38	56	60	25	70	70	91	13	37	1	1	0

[a)] For $s = 0$, {B,C} is selected.
[b)] For $s = 1$, {A,B} is selected.

Notes: Darker shades of blue indicate higher frequencies. The numerical percentage appears within each shaded cell. The profile numbering is the same as for Table 1.

Patterns for profiles 1 and 2 anticipate our overall conclusions. If, just for the moment, we confine attention to scoring rules and the Condorcet top-cycle extension, we would infer that 86% of subjects use scoring rules with $s > \frac{1}{3}$ (because they choose A in profile 1), that only 2-3% of subjects use scoring rules with $s < \frac{1}{3}$ (because they choose B or C in profile 2), and that 10% of subjects use the Condorcet rule (because the fraction of A increases from 86% to 96% between profiles 1 and 2).

Choices for profiles 12 and 13 corroborate the low prevalence of the Condorcet rule, in that we see little indication of indeterminacy despite the presence of cycles. For profile 12, 91% of subjects agree on option C, which is rank-dominant, and for profile 13, 73% of subjects select option A, which minimizes the number of last-place ranks.

Choices for profiles 3, 4, and 5 corroborate the prevalence of concave scoring rules, which select options C (64%), A (63%), and B (75%), respectively. In contrast, all convex scoring rules and the Condorcet rule select options A (36%), B (37%), and C (24%). Either pattern is consistent with the Borda rule, which is only partially resolute for these profiles.

4.2 Main classification

4.2.1 Classification procedures

Next we classify individual subjects according to the social choice rules they appear to use. We deploy two Bayes classification procedures (Hastie et al., 2001), which assign each subject to the rule with the greatest posterior probability conditional on her observed choices under distributional assumptions detailed below.[43]

The first Bayes classification procedure only relies on consequential choices (i.e., it excludes information on indifference). The data for each subject then consists of 17 options, one for each preference profile. We make the following four assumptions (analogously to Costa-Gomes et al., 2001): (i) The prior distribution over pre-specified rules is uniform. (ii) For each of the 17 outcomes, the subject follows her assigned rule with probability $1 - \epsilon$, and uniformly randomizes over the three options with probability ϵ, where ϵ is distributed uniformly over $[0, 1]$. (iii) Decision errors are independent across preference profiles.[44] (iv) When a rule is irresolute, the subject randomizes uniformly over the prescribed choices.[45] We assign each subject the rule R^* and noise level ϵ^* that maximize this posterior probability, $P(R, \epsilon|c)$, where c is their choice vector.[46] When more than one rule maximizes the Bayesian posterior, we assign the subject to a maximizing rule at random.

When limiting consideration to consequential choices, irresolute rules have a built-in advantage: their predictions more easily encompass actual choices. Our first procedure creates a countervailing disadvantage: irresolute rules receive less "credit" (in terms of the increment to the posterior probability) than resolute rules when both turn out to be consistent with a given choice.[47]

The second Bayes classification procedure employs subjects' indifference statements along with their consequential choices. The data for each subject then consists of 17 subsets of optimal options, one for each preference profile. We continue to impose assumptions (i) and (iii), along with a slightly modified version of assumption (ii) (when deviating from her rule, the subject randomizes uniformly over the seven subsets of options, rather than the three options). Under these assumptions, a rule

[43] Simulations show that maximum-likelihood approaches perform poorly, in large part because they exhibit extreme bias towards less resolute rules in our setting. In contrast, the Bayes classifier performs well in simulations (see Appendix B.2).

[44] With this type of independence assumption, the method is sometimes called the *Naïve* Bayes Classifier.

[45] Because our displays present alternatives and workers in random order (redrawn in each round), even positional criteria (such as always choosing the option on the left) will yield uniform distributions.

[46] See Appendix B.1 for the explicit derivation of $P(R, \epsilon|c)$. This procedure is known as the Maximum A Posteriori (MAP) decision rule. The robustness of Bayesian classifiers has been documented extensively (see, e.g., Webb, 2010).

[47] This observation reflects the more general principle of the Bayesian Occam's Razor (see MacKay, 2003).

maximizes the posterior probability if and only if it maximizes the number of profiles for which it predicts the correct subset. As with our first procedure, we break ties at random.

The two procedures complement each other. On the one hand, restricting attention to consequential choices may yield more reliable results. On the other hand, the indifference data provide pertinent information, particularly inasmuch as the average Social Planner expresses irresoluteness for 18.01% of the profiles (just over 3 of 17).[48] Information on indifference also allow us to dispense with assumption (iv).

We pre-specify the 22 benevolent social choice rules discussed in Section 2.2. We also include a malevolent versions each rule by inverting each Stakeholder's preference ranking before applying the rule. Accordingly, we consider a total of 44 possible aggregation rules.

For our first classification procedure, we absorb the following three scoring rules into neighboring intervals: $s = \frac{3}{5}$, $s = \frac{4}{5}$, and $s = 1$; we do the same with their malevolent counterparts. The reason is that we cannot separately identify these rules without using information on indifference. As shown in Figure 2, each differs from nearby scoring rules on exactly one profile. Moreover, for the single differentiating profile, each prescribes the union of the options selected when the scoring parameter is slightly larger, and when it is slightly smaller. Because our first procedure always favors resoluteness over irresoluteness when both possibilities are consistent with the same observation, it will never select $s \in \{\frac{3}{5}, \frac{4}{5}, 1\}$ over all nearby scoring rules. In contrast, because there are *two* profiles for which the scoring rule with $s = \frac{1}{3}$ is irresolute while its neighbors are resolute, that rule can rationalize certain choice patterns that are inconsistent with its neighbors. A similar observation holds for $s \in \{0, \frac{1}{2}, \frac{2}{3}, \frac{3}{4}\}$.

4.2.2 Classification results

Figure 7 displays our main classification results. Panel A, which relies on incentivized choices alone, is strikingly similar to Panel B, which also incorporates indifference data. The following salient features merit emphasis.

First, the two most common aggregation methods are the Borda rule and the near-antiplurality rule (with $4/5 < s < 1$). Together, these rules account for 30 to 40 percent of all subjects, depending on the classification procedure.

Second a clear majority of all subjects (62.5% in Panel A, and 61.5% in Panel B) follow *strictly concave scoring rules* with $\frac{1}{2} < s \leq 1$. In contrast, strictly *convex* scoring rules ($s < \frac{1}{2}$) are unpopular. Surprisingly few subjects follow plurality rule (1% in Panel A, and 0.25% in Panel B.)

Third, fewer than 5% of subjects choose consistently with the Condorcet rule, and virtually no subjects follow other p-supermajority rules (supermajority and unanimity). A small minority follow scoring runoff rules (4.7% in Panel A and 7.2% in Panel B).

[48]In comparison, the set of our benevolent pre-specified rules produce a tie for 23.8% of the profiles, on average. Focusing only on the Condorcet rule and the set of all scoring rules we can identify, this figure falls to 14.3%. Social Planners designate all options as equally good for only 1.54% of profiles.

Because our pre-specified rules contain only one Condorcet extension (top cycle), these classifications could in principle understate the prevalence of rules in the Condorcet class. We therefore enlarge the set of pre-specified rules to include *all conceivable* Condorcet extensions, and reclassify subjects using our first procedure.[49] We find that 10.6% of subjects use a Condorcet extension, a modest increase, some of which would occur by chance.[50] It is unlikely that the low prevalence of Condorcet reasoning is a statistical or experimental artifact, because the Condorcet rule coincides on a large number of profiles with convex scoring rules, which are also unpopular. We provide further corroboration of this finding based on four-option problems in section 4.4.

Fourth, we see little if any evidence that subjects are either malevolent or lazy. The fraction of subjects assigned to malevolent rules is de minimis. Lazy subjects would be inclined to select the most easily implementable rule. Plurality rule is arguably the least cognitively demanding alternative, followed by plurality runoff, yet the vast majority of subjects evidently find both of these rules unappealing. As we have noted, most subjects employ strictly concave scoring rules which, with the exception of antiplurality, require more nuanced and complex judgments.

We obtain similar results for each method of presenting preference profiles. The only notable difference across display formats is that Borda is more common than near-antiplurality with the first and third display formats, while the opposite is true for the second display format; furthermore, this difference is larger when we use the indifference data (see Appendix C.1).

Random benchmark We draw statistical inferences by comparing our classification to a random-choice benchmark. We construct the benchmark by generating 4,000 artificial subjects whose simulated selections for each profile are uniformly distributed across options. We generate indifference data by designating each of the unchosen options as equally good based on independent Bernoulli draws. We choose the Bernoulli probability to match the average size of the best-option sets according to the actual subjects. We then assign each simulated subject to a pre-specified social choice rule using both of our procedures. We construct the distribution of subjects assigned to each rule under the null hypothesis of random choice by drawing 1,000 bootstrap samples of 405 simulated subjects each.

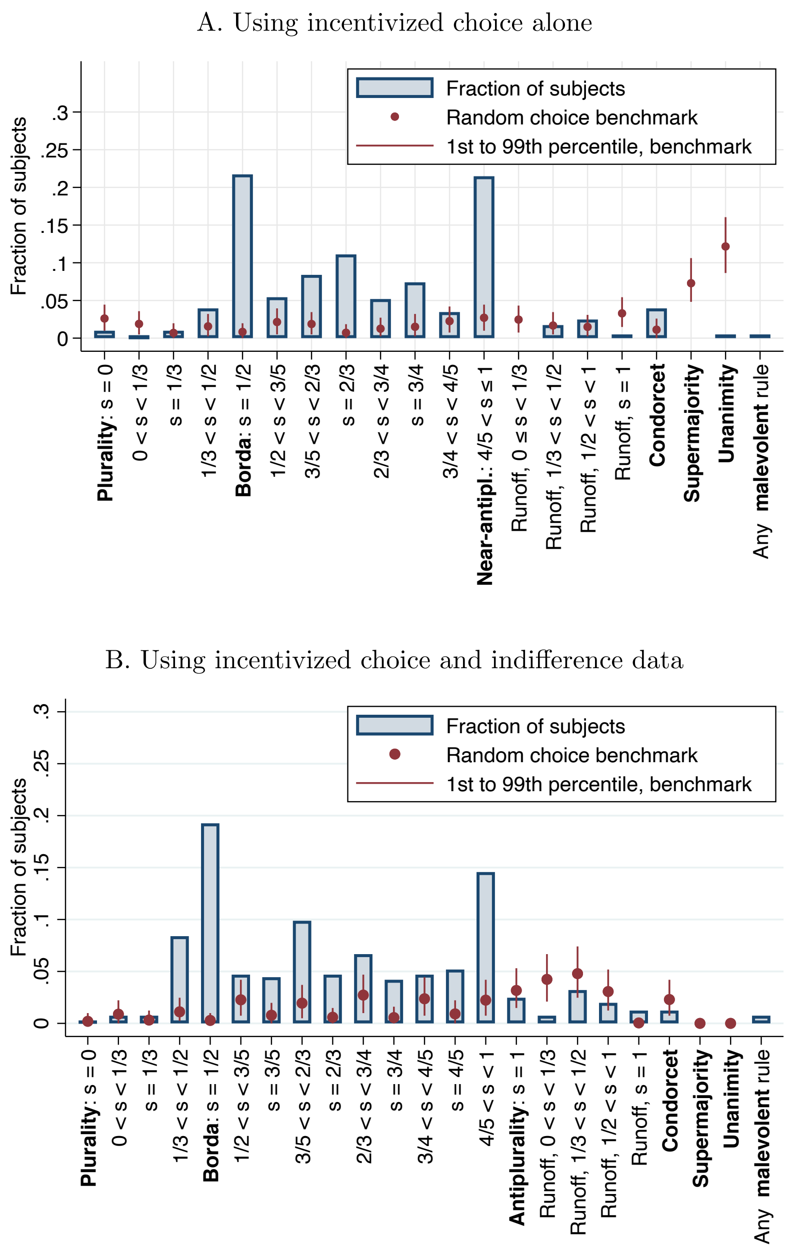
Figure 7 plots, for each rule, the mean fraction of simulated subjects assigned to that rule, as well as the 1st and 99th percentiles of the corresponding distribution. The average fractions of simulated subjects assigned to a malevolent rule is 50.4% in panel A and 40.9% in panel B, which exceed the ranges of the figures.[51] Turning to benevolent rules, in panel A we see that the fraction of subjects

[49] Because Condorcet winners fail to exist for two of the 17 profiles, there are only nine resolute Condorcet extensions. As long as we include all of them, there is no need to add any irresolute Condorcet extensions, because our first procedure never assigns a subject to a less resolute rule that is equally consistent with the subject's choices (Bayesian Occam's Razor).

[50] The incremental subjects assigned to a Condorcet extension were originally assigned to a heterogeneous set of rules.

[51] Because our selection of profiles is not random, these benchmarks can deviate from 50%. To see this point, consider the example of profile 1. Only the choice of the rank-dominated alternative B is consistent with a malevolent scoring rule. Hence, one third of uniformly random choices would be classified as consistent with a malevolent scoring rule based on that profile alone. The same argument applies to each of our score-identifying profiles. These constitute a larger fraction of all profiles in the political domain than in the work domain.

Figure 7: Best fitting pre-specified rules



Notes: Both panels show the frequency of subjects classified as following each pre-specified rule (blue bars). Each red dot indicates the fraction of 4,000 simulated subjects who randomize uniformly that the pertinent method classifies as a particular pre-specified type. From that sample of 4,000 simulated subjects, we draw 1,000 bootstrap samples of 405 subjects each to a construct a distribution of classifications. The red lines extend from the 1st to the 99th percentiles of that distribution. The random-choice benchmark for malevolent rules is not visible as it exceeds the range of the graph (50.4% and 40.9% in the work and political domains, respectively) .

assigned to every weakly concave scoring rule except $\frac{3}{4} < s < \frac{4}{5}$ exceeds the 99th percentile of the random benchmark. In contrast, the fractions of subjects assigned to the two most convex scoring rules ($s < \frac{1}{3}$) fall short of the 1st percentile of the random benchmark. While the fraction of subjects assigned to the Condorcet rule is small, it is larger than we would observe by chance, a conclusion for which we find corroboration in Section 4.4. Finally, scoring runoff rules, supermajority, and unanimity are no more prevalent (and in some cases significantly less prevalent) than for the random-choice benchmark. Similar conclusions generally follow from panel B, with the qualification that the random-choice simulations assign lower frequencies to scoring rules that coincide with the boundaries of distinguishable intervals.

Because our two classification procedures yield such similar results, for the sake of brevity we focus on the first procedure in subsequent sections.

Goodness of fit The average value of the estimated noise parameter ϵ^* provides a formal goodness-of-fit measure. Using incentivized choices alone, we obtain a mean noise parameter of 0.10, which signifies that the average subject chose randomly in just 1.7 of the 17 preference profiles. A whopping 42.0% of our subjects fit their assigned rule perfectly. For the remainder, the mean noise parameter is 0.16, equivalent to choosing randomly for 2.7 of the 17 preference profiles.[52] In contrast, the average estimated noise parameter for our simulated random-choice data is 0.46, and 0.57 when excluding simulated subjects classified as Supermajority or Unanimity (10 of 17 profiles).[53] When we use the indifference data, subjects' responses match the sets of options selected by their assigned rule for 14 of 17 profiles (85%). In contrast, for our random-choice benchmark, the corresponding number is 44%.[54] The fact that actual choices fit the rules dramatically better than random-choice simulations also indicates that the vast majority of our subjects paid attention and chose thoughtfully.

A more detailed picture of goodness of fit emerges from comparisons between the theoretical fingerprints associated with particular rules and the empirical fingerprints of the subjects assigned to those rules. The top half of Figure 8, panel A, plots the distribution of choices, by profile, for subjects classified as using the Borda rule. The bottom half of the same panel shows the Borda prescriptions. The fit is plainly tight. The highest choice frequency for any Borda-proscribed option is 16% (profile 6, option B). The second highest is 8% (profile 1, option C). The frequencies of all other Borda-proscribed options are at most 5%. While these subjects rarely depart from the Borda

[52] Appendix C.2 shows classifications of subjects based on the incentivized data split according to whether they fit their assigned rules perfectly or imperfectly. While the distributions are generally similar, Borda is more prevalent relative to near-antiplurality for perfectly fitting subjects. This pattern is mechanical: because Borda is less resolute than near-antiplurality, it has more scope for matching choice patterns perfectly.

[53] The mean estimated noise parameter in the random-choice data never equals its actual value (unity) because some random-choice sequences will always match some choice rules relatively well. The downward bias in the estimates of ϵ reflects overfitting.

[54] Alternatively, one can think of an empirical fingerprint as consisting of $3 \times 17 = 51$ binary variables, each of which indicates whether a given option is selected for a given profile. The average subject's choice coincides with the prediction of the best-fitting rule in 47 of these 51 cases (92%), which is far higher than the random-choice benchmark (65.9%).

Figure 8: Empirical fingerprints of classified subjects

A. Subjects classified as Borda

Empirical Choices

A	92	99	66	44	0	0	1	0	95	5	0	0	49	0	1	0	0
B	0	0	0	56	60	16	5	5	0	0	3	2	27	66	99	98	100
C	8	1	34	0	40	84	94	95	5	95	97	98	24	34	0	2	0

Rule prediction

A	100	100	50	50	0	0	0	0	100	0	0	0	33	0	0	0	0
B	0	0	0	50	50	0	0	0	0	0	0	0	33	50	100	100	100
C	0	0	50	0	50	100	100	100	0	100	100	100	33	50	0	0	0

B. Subjects classified as near-antiplurality

Empirical Choices

A	95	100	9	85	1	0	0	0	32	85	0	0	97	1	9	0	0
B	0	0	0	15	98	100	84	87	5	0	100	3	2	59	90	100	100
C	5	0	91	0	1	0	16	13	63	15	0	97	1	40	1	0	0

Rule prediction

A	100	100	0	100	0	0	0	0	0	100	0	0	100	0	0	0	0
B	0	0	0	0	100	100	100	100	0	0	100	0	0	50	100	100	100
C	0	0	100	0	0	0	0	0	100	0	0	100	0	50	0	0	0

Notes: In both panels, the top half displays the choices by subjects assigned to a certain rule. The bottom half displays the choices the rule predicts. The figures pertain to the classification procedure that does not use indifferent data. Darker shades of grey indicate higher frequencies. The numerical percentage appears within each shaded cell. For the theoretical rule, we take the frequency of each best option to be 50% for a two-way tie and 33% for a three-way tie.

rule, they do deviate somewhat from uniform resolution of ties (see, for example, profiles 3 and 14, where the proportions are one-third/two-thirds rather than half-half).

Panel B of Figure 8 provides analogous information for the near-antiplurality rule, which differs from Borda on 10 of the 17 profiles. The fit is also good, if slightly less tight. The highest choice frequency for any antiplurality-proscribed option is 32% (profile 9, option A). These subjects select four other proscribed options with frequencies ranging between 13% and 16% (see profiles 4, 7, 8, and 10), but they select each of the remaining 28 proscribed options with frequencies of 5% or less.

Overall, the 22 pre-specified benevolent social choice rules fit the data remarkably well given that there are more than 232 trillion (7^{17}) possible rules for this restricted set of 17 profiles, of which more than 18 trillion ($7^{14} \times 3^3$) are "reasonable" in the sense that they exhibit no Pareto violations. To further allay possible concerns about overfitting, we show in subsection 4.5 that our classification predicts well out of sample.

4.3 Is the classification complete?

To determine whether our classification analysis excludes empirically important rules, we look for clusters of subjects whose choices more closely resemble each others' than any of the pre-specified possibilities. Our approach is similar to that of Costa-Gomes and Crawford (2006).

To identify clusters, we use the k-modes clustering algorithm, which is an adaptation of the well-known k-means method to categorical data (Huang, 1998). The algorithm begins by arbitrarily selecting k subjects as initial cluster centers. Then it iterates two steps. First, each subject is assigned to the cluster for which the center matches her choices on the largest number of preference profiles. Second, cluster centers are updated: the new cluster center consists of the modal choice for subjects assigned to that cluster.[55] The algorithm terminates once the cluster centers stabilize. We use our pre-specified rules to create additional potential cluster modes that appear in all iterations. Because we do not use the indifference data for this exercise, we include every resolute version of each pre-specified rule. Following Costa-Gomes and Crawford (2006), if a subject is equidistant from a pre-specified rule and an endogenous cluster, we assign them to the pre-specified rule.

We search for clusters in the work domain fixing $k = 1, 2, 3, 5$, and 10. For $k = 1$, we run the algorithm 405 times, using each subject's choices as an initial cluster center once. For $k \geq 2$, we run the algorithm 1000 times, in each case randomly setting the initial cluster centers equal to the choices of k randomly selected subjects (excluding those who perfectly conform to pre-specified rules), and retaining the solution with the lowest total within-cluster distance.[56] We limit the pre-specified rules to all scoring rules and all Condorcet extensions, which have a total of 296 resolute components. We exclude unanimity because the resolute components (of which there are $2^3 \times 3^{14} > 38 \times 10^6$) encompass all choice patterns that are consistent with the Pareto principle. Similarly, we exclude supermajority

[55] In our setting, the modal choice is a vector specifying the most common selection for each preference profile.

[56] We use the Hamming distance, i.e. the number of profiles on which two choice sequences differ from each other.

because it is massively irresolute, so the number of resolute components is enormous. These exclusions are likely inconsequential given the small number of subjects assigned to these rules in section 4.2, and in any case the exclusion of an empirically important rule can only increase the fraction of subjects assigned to endogenous clusters. Other exclusions are attributable to redundancies.[57]

Table 5 displays the resulting endogenous clusters and the fractions of subjects assigned to each of them. For $k = 1$, just under 5% (19 of 405) of subjects are assigned to an endogenous cluster. For $k = 2$, the same cluster emerges plus a second that attracts under 2% of subjects (7 of 405). As we increase k further, these same two clusters remain, and the others encompass even fewer subjects. For $k = 10$, the smallest three clusters are degenerate (1 subject), indicating that we can find no other consequential similarities. Notably, the rule for the largest cluster is a one-profile deviation from near-antiplurality, from which it departs on profile 9 by selecting option A rather than C. We note that this is the only profile for which near-antiplurality selects an option ranked last by some Stakeholder, and not ranked first by any other Stakeholder.

4.4 Corroboration based on four-option social choice problems

Four-option profiles provide additional opportunities to distinguish cleanly between classes of social choice rules. Specifically, there are two four-option profiles, labeled "Condorcet-separating 1" and "Condorcet-separating 2" in Table 3 (numbered 18 and 19), for which the Condorcet winner is *rank-dominated*. These profiles distinguish between all Condorcet extensions and the entire class of *proper* scoring rules (ones that do not assign the same score to any two ranks) because the former must select the Condorcet winner while the latter cannot select a rank-dominated option.

We randomly intermingle both of these profiles with the three-option profiles in both domain blocks. While four-option problems are more cognitively demanding, recall that the experimental interface allows subjects to hide options, which makes it easy to identify Condorcet winners.

As shown in the left half of Table 4 (which pertains to the work domain), subjects choose the Condorcet winner roughly one-fifth of the time for each of these profiles. However, only 11.6% consistently choose the Condorcet winner for both profiles.[58] In contrast, because a negligible fraction of subjects choose option D, roughly 80% of the individual choices are consistent with a proper scoring rule. Moreover, for 69.6% of subjects, the pair of choices is consistent with some scoring rule in the following class: $[1, s_1, s_2, 0]$ where $s_1 = (2/3)^\gamma$, $s_2 = (1/3)^\gamma$, and $\gamma \in [0, \infty]$.[59]

In interpreting the preceding results, it is important to bear in mind that rules outside the Condorcet class can rationalize the selection of option A for profiles 18 and 19. As indicated in Table 3, plurality rule ($s_1 = s_2 = 0$) prescribes options A and B, while the plurality runoff rule prescribes

[57] For example, because plurality runoff always selects a plurality winner, the resolute components of the latter rule contain those of the former.

[58] This frequency, while relatively small, is significantly higher than would be observed by chance if the distributions of choices were independent across profiles, $0.205 \times 0.212 = 0.043$ (χ^2-test, $p < 0.001$).

[59] This class of rules is consistent with choosing B for both profiles, choosing C for both profiles, and (for a threshold value of γ) choosing B in one and C in the other.

Table 3: Four-alternative profiles.

Label	Index	Profile	Option selected by some proper scoring rule	Condorcet	Plurality (* = runoff)
Condorcet-separating 1	18	A A B B C B B A C D C C C D A D D D A B	B or C	A	{A*,B}
Condorcet-separating 2	19	A A B B C B B A D D C C C C A D D D A B	B or C	A	{A*,B}
Runoff-separating 1	22	A A B D D B B C A C C C D C B D D A B A	A or B or C	{A, B, C, D}	{A,D*}
Runoff-separating 2	23	A A C D D B B B A B C C D C C D D A B A	A or B or C	{A, B, C, D}	{A,D*}

Notes: Each preference profile is displayed as a 4×5-matrix; columns correspond to workers, rows correspond to preference ranks. A worker's r-ranked alternative is listed in the rth row. For Condorcet-cyclical profiles, we indicate the set of options in the top-cycle.

Table 4: Choices on class-separating profiles

Domain	Work				Politics			
Option	A	B	C	D	A	B	C	D
Condorcet winner	✓				✓			
Optimal for some scoring rule		✓	✓			✓	✓	
Condorcet-separating 1	0.205	0.694	0.099	0.002	0.188	0.746	0.064	0.002
Condorcet-separating 2	0.212	0.719	0.064	0.005	0.188	0.800	0.012	0.000
Consistent Condorcet	0.116				0.111			
Consistent Scoring	0.696				0.733			
Option	A	B	C	D	A	B	C	D
Plurality-runoff winner				✓				✓
Optimal for some scoring rule	✓	✓	✓		✓	✓	✓	
Runoff-separating 1	0.257	0.385	0.314	0.044	0.353	0.405	0.188	0.054
Runoff-separating 2	0.202	0.615	0.141	0.042	0.259	0.643	0.042	0.056
Consistent Runoff	0.012				0.028			
Consistent Scoring	0.884				0.930			

Notes: This table displays the fraction of subjects choosing each of the four options in each of the class-separating profiles. The first 262 subjects were not presented with the profile labelled Runoff-separating 2 in the political domain. The fraction of subjects consistently choosing in accordance with the plurality runoff rule in that domain is based on the remaining subjects.

Table 5: Clustering results

Profile	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Condorcet	C	A	A	B	C	C	C	C	A	C	C	ABC	ABC	B	B	B	B
Scoring																	
$\bar{s}$	1/3	1/3	1/2	1/2	1/2	3/5	2/3	2/3	3/4	3/4	4/5	-	1/2	0	0	0	0
$s < \bar{s}$	C	B$^{a)}$	A	B	C	C	C	C	A	C	C	C$^{a)}$	BC	-	-	-	-
$s > \bar{s}$	A	A	C	A	B	B	B	B	C	A	B	C	A	BC	B$^{b)}$	B	B
	Endogenous clusters, $k = 1$																
% subjects																	
4.69	A	A	C	A	B	B	B	B	A	A	B	C	A	B	B	B	B
Total: 4.69																	
	Endogenous clusters, $k = 2$																
% subjects																	
4.69	A	A	C	A	B	B	B	B	A	A	B	C	A	B	B	B	B
1.73	A	A	C	B	B	B	C	B	C	C	B	C	A	C	B	B	B
Total: 6.42																	
	Endogenous clusters, $k = 3$																
% subjects																	
4.69	A	A	C	A	B	B	B	B	A	A	B	C	A	B	B	B	B
1.73	A	A	C	B	B	B	C	B	C	C	B	C	A	C	B	B	B
0.25	A	A	C	A	A	A	B	A	B	A	A	B	A	A	C	B	A
Total: 6.67																	
	Endogenous clusters, $k = 5$																
% subjects																	
4.69	A	A	C	A	B	B	B	B	A	A	B	C	A	B	B	B	B
1.73	A	A	C	A	B	B	B	B	A	A	B	C	A	C	B	B	B
1.73	A	A	C	B	B	B	C	B	C	C	B	C	A	C	B	B	B
1.48	A	A	A	B	B	B	B	C	A	C	C	C	A	C	B	B	B
0.74	A	A	A	A	B	B	B	C	B	A	B	C	A	A	C	B	B
Total: 10.37																	
	Endogenous clusters, $k = 10$																
% subjects																	
4.69	A	A	C	A	B	B	B	B	A	A	B	C	A	B	B	B	B
1.73	A	A	C	B	B	B	C	B	C	C	B	C	A	C	B	B	B
1.48	A	A	A	B	B	B	B	C	A	C	C	C	A	B	B	B	B
1.23	A	A	A	B	B	B	C	C	A	C	C	C	A	B	B	B	B
0.99	A	A	C	A	B	B	C	C	C	C	C	C	A	C	B	B	B
0.74	A	A	C	A	B	B	C	B	A	C	C	C	C	B	B	B	B
0.74	A	A	C	A	B	B	B	C	C	C	B	C	A	B	B	B	B
0.25	A	A	C	A	A	A	B	A	B	A	A	B	A	A	C	B	A
0.25	B	C	B	B	A	B	C	C	C	B	A	A	B	A	C	A	B
0.25	A	C	A	B	C	C	B	B	A	A	B	C	A	B	C	C	B
Total: 12.35																	

Notes: This table shows the clusters which endogenously emerge in addition to our pre-specified rules from application of a k-modes algorithm, along with the fractions of subjects assigned to each such cluster. For ease of comparison, the top section of the table shows the choices of selected pre-specified rules.

A. Antiplurality rule ($s_1 = s_2 = 1$) also prescribes either A or B. One way to distinguish between Condorcet and plurality runoff on the one hand, and plurality and antiplurality on the other, is to examine the indifference data. Of those who select A for both profiles, 36.2% rate B as equally good, which suggests that more than a third of these selections reflect either plurality or antiplurality rule. It is also noteworthy that only 51.1% of these same subjects choose option C for profile 1 (consistent with both Condorcet and plurality rule), and also choose A, the Condorcet winner, rather than B or C, the plurality winners, for profile 2. Accordingly, choices for our four-option profiles imply that the fraction of subjects who implicitly follow some Condorcet rule in the work domain is on the order of 6% to 7%, which is consistent with our findings for three-option problems.

Profiles 22 and 23 in Table 3, which we also intermingled with the three-option profiles, leverage the principle of rank-dominance to provide clean separation between proper scoring rules and the plurality runoff rule. As shown in the left half of Table 4, subjects choose option D, the plurality runoff winner, roughly 5% of the time. Only 1.2% of subjects choose D for both profiles,[60] whereas 88.4% of subjects behave as if both choices reflect a single proper scoring rule from the family specified above.[61] Accordingly, only a small fraction of the Condorcet-consistent behavior for profiles 18 and 19 is likely attributable to use of the plurality runoff rule.

Four-option profiles such as 22 and 23 also enable more nuanced distinctions among rules. For example, they can provide a foundation for distinguishing concave scoring from a general aversion to lowest ranks; see Appendix C.3.

4.5 Contextual judgments or structural aggregation principles?

Next we investigate the extent to which our classification captures subjects' structural aggregation principles, as opposed to contextual judgments.

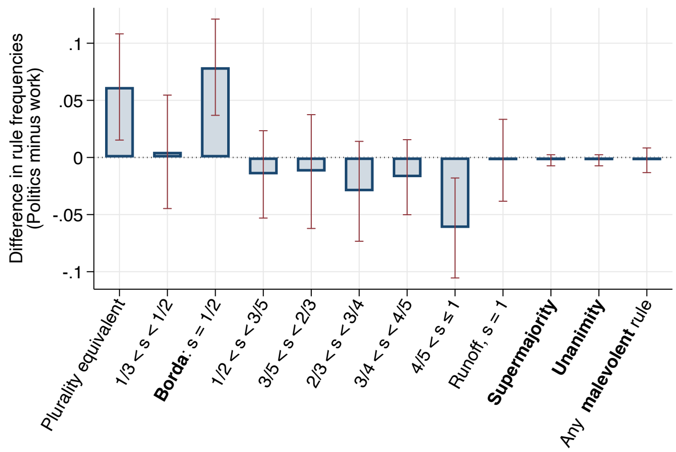
To the extent we have uncovered subjects' structural aggregation principles, we would expect our classifications to be stable across the work and political domains. Recall that, for the latter, we present subjects with a smaller number of preference profiles (7 instead of 17). While we can still identify scoring rules for which the parameter falls within the same intervals as before, we can no longer separately identify rules for which it lies at the boundaries of those intervals (i.e., points in $\mathcal{C}$).[62] Moreover, the fingerprints of scoring rules with $s \leq \frac{1}{3}$ (including plurality rule), the Condorcet rule, and all scoring runoff rules with $s < 1$ coincide for these seven profiles. For our current purposes, we will call this group the "plurality-equivalent rules."

[60] Though small, this fraction is significantly higher than would be observed by chance if the distributions of choices were independent across profiles (χ^2-test, $p < 0.001$).

[61] For these two profiles, every combination of choices in {A,B,C} is consistent with some scoring rule, except that a choice of option C in profile 23 implies $\gamma \geq 0.69$, and, accordingly, that C is also the best choice for profile 22.

[62] As explained in Section 4.2, consequential choice data can identify such scoring rules only if the two nearby scoring rules $s + \epsilon$ and $s - \epsilon$ differ on at least two preference profiles. Appendix A.2 shows the distance between all pairs of pre-specified rules in the political domain.

Figure 9: Comparison between work and political domains



Notes: Classifications are based only on consequential choices, and on the same set of seven preference profiles for both domains. The category 'plurality equivalent' includes scoring rules with $s \leq 1/3$, the Condorcet rule, and all scoring runoff rules with $s < 1$.

Figure 9 shows the differences in the resulting distributions of classifications for the work and political domains. Here we rely only on consequential choices, and we reclassify subjects in the work domain based on the same seven preference profiles to ensure comparability. Systematic differences are immediately apparent. Within the political domain, subjects are less likely to use strictly concave scoring rules, especially $\frac{4}{5} < s \leq 1$, and are more likely to use either the Borda rule or a plurality-equivalent rule. The difference is highly statistically significant (Wilcoxon signed-rank test, $p < 0.01$).[63] It bears emphasis, however, that these differences are of limited magnitude. The increase in the frequency of plurality-equivalent rules is on the order of 6%, and the decrease in the frequency of all strictly concave rules is 13.6%.

Even if aggregation rules are not completely stable across domains, they may still capture stable tendencies that reflect underlying structure. Notably, results for the four-option class-separating profiles in Table 4 exhibit strikingly little domain sensitivity.[64] It follows that people are generally attracted to scoring rules and generally averse to majoritarian criteria.

To evaluate the stability of aggregation preferences more comprehensively, we examine the out-of-sample and cross-domain predictive power of our classifications. For each evaluation, we designate a training set of preference profiles which we use to classify Social Planners based on their consequential choices, as well as a test set which we use to evaluate predictive success. We score predictions as follows. If the actual choice lies outside the predicted best-choice set, the score is zero. If it lies within

[63] We apply the test to the 400 (out of 405) subjects who are classified as following a scoring rule or a plurality-equivalent rule in both domains.

[64] While all subjects saw profile 23 in the work domain, only those in Sessions 8 - 11 saw it in the political domain.

the predicted best-choice set, the score is 1, $\frac{1}{2}$, or $\frac{1}{3}$ depending on whether there are 1, 2, or 3 best options. With this scoring system, if underlying choices are in fact uniformly random, the average score will be $\frac{1}{3}$ irrespective of the sizes of predicted best-choice sets. Averaging this score across all profiles in the test set, we obtain a measure of predictive accuracy that lies between 0 and 1.

We conduct four separate evaluations, two involving within-domain predictions, and two involving cross-domain predictions. For the within-domain predictions, we use leave-one-out-cross-validation (LOOCV): we designate one preference profile in the pertinent domain as the test set and use the other same-domain profiles as the training set. We repeat using each profile as the test set and average the predictive scores. For cross-domain predictions, we designate all profiles in one domain as the training set and all profiles in the other domain as the test set. Thus, the training set for the work domain consists of either 16 (within-domain) or 17 (cross-domain) profiles, while the training set for the political domain consists of either 6 (within-domain) or 7 (cross-domain) profiles.[65] Because of these differences, caution is warranted when comparing the various predictions to each other rather than to benchmarks.

As shown in Table 6, the average predictive accuracy scores for our four evaluations range from 0.758 (work to politics) to 0.853 (work to work). In all four cases, predictive performance is far superior to the random-choice benchmark (expected score of $\frac{1}{3}$).

Next we quantify the improvement in predictive performance that results from making appropriate assignments of subjects to pre-specified rules, rather than merely from pre-specifying a set of rules that generally coincide with reasonable tendencies. To this end, we offer three alternative benchmarks. For the first, we make predictions based on a uniform random assignment of each subject to one of the 44 pre-specified rules. The second benchmark is identical, except that we restrict these assignments to the 22 benevolent rules. The third refines the second by randomizing based on the estimated distribution of subjects across rules, rather than uniformly. There are two versions of the third benchmark, which differ according to whether we use the estimated distribution for the work domain or the political domain. In each case, we perform the procedure using 1000 bootstrap draws of our sample, and report both the mean and the 99th percentile of the resulting score.

For all four evaluations and all benchmarks, the average predictive accuracy score exceeds the 99th percentile of the benchmark's distribution by a wide margin. To be sure, merely pre-specifying a set of rules that generally coincide with reasonable tendencies accounts for a sizable portion of the improvement in predictive accuracy relative to the random-choice benchmark. However, the gain from making appropriate assignments of individual subjects to specific rules is considerable. To illustrate, focus on the most demanding benchmark for the work domain (3a), for which the mean benchmark score is 0.762. If all of our individual-level assignments were correct, we would obtain a score of 0.921. This number represents the theoretical maximum for the average score, given the

[65] For the purpose of predicting from the political domain to the work domain, when the worker's classification encompasses more than one of the 22 pre-specified rules (such as the plurality-equivalent rules), we select one of them at random.

Table 6: Out-of-sample predictive power of the Bayesian classification

	(1)	(2)
Dependent variable	Fraction of correct predictions (weighted by resoluteness)	
Test domain	Work	Politics
Predictions		
Training domain		
Work	0.853	0.758
Politics	0.812	0.759
Benchmarks		
1. Uniform, all prespecified rules		
Mean	0.445	0.398
99th percentile	0.485	0.440
2. Uniform, non-malevolent prespecified rules		
Mean	0.720	0.651
99th percentile	0.744	0.686
3.a Estimated rule frequencies, work domain		
Mean	0.762	0.653
99th percentile	0.779	0.680
3.b Estimated rule frequencies, political domain		
Mean	0.696	0.625
99th percentile	0.716	0.652

Notes: Within-domain predictions are based on leave-out-one cross-validation.

overall distribution of pre-specified rules; it is less than 1.0 because the rules are partially irresolute. An average score of 0.853 therefore implies that the individual-level assignments achieve 57% (i.e., $(0.853 - 0.762)/(0.921 - 0.762)$) of the maximum possible gain in predictive accuracy over a baseline that randomly scrambles those assignments.

Based on the strong out-of-sample predictive performance of our classifications, we conclude that assigned rules capture the essence of subjects' actual aggregation criteria. While the shift in the distributions of selections between the two domains points to a degree of context-specificity, the accuracy of the cross-domain predictions reassures us that ordinal aggregation also entails stable structural elements.

4.6 Do Social Planners make cardinal inferences?

Why are scoring rules so popular? One possibility is that people are comfortable with the concept of cardinal utility, so they use the ordinal information they receive to make cardinal inferences before aggregating and making a selection (in the spirit of Apesteguia et al., 2011). This hypothesis is consistent with the context-sensitivity of scoring rules documented in section 4.5, but that finding may have other explanations. In this section, we provide additional evidence that corroborates the cardinal inference hypothesis.

Informational interventions Suppose a decision maker chooses option A from the set $\{A, B, C\}$. According to the choice axiom known as Sen's α, if we remove option C from the opportunity set, the chooser will still select A. In the current context, there are two distinct ways to remove C: we can continue to inform the Social Planner about the Stakeholders' rankings of all three options even though C is no longer available (variant 1), or we can limit this information to the rankings of A and B (variant 2). Imagine that, in the original problem, the Social Planner makes cardinal inferences about the attractiveness of options A and B from their rankings relative to C and applies a Samuelson-Bergson social welfare function. In variant 1, that information remains available, so the Planner should respect Sen's α. However, in variant 2, that information is no longer available, so depending on the rankings, we should see violations of Sen's α.[66]

Each column of Table 7 provides a separate test of the cardinal-inference hypothesis based on this design. For column (1), the "Baseline" profile (part A) consists of three alternatives. Option C is obviously inferior, and is almost never chosen. For the "Option removed, rank information retained" profile (part B), we remove option C from the menu but continue to display rankings that include it. Choice frequencies are similar and the differences are statistically insignificant, so we do not reject Sen's α. For the "Option and rank information removed" profile (part C) we remove option C from the menu and from the Stakeholders' rankings. Choice frequencies change dramatically, and we resoundingly reject Sen's α. The natural explanation is that Stakeholders generally regard C as a bad option. The fact that one of them thinks B is worse than C, whereas none think A is worse than C, leads most Social Planners to choose A over B. But when that information is removed, nearly all Social Planners select B based on the majority preference relationship.

Results for the other two columns in Table 7 are qualitatively similar. In column (2), where we remove option A from a three-alternative profile, we reject Sen's α even when information about the rankings of A remains available, but the choice frequencies do not change dramatically, especially compared with the outcome when we also remove A from the rankings. In column (3), where we remove option D from a four-option profile, the choice frequencies barely change when information about the rankings of D remain available, but change dramatically when they are unavailable.

Synthetic money-metric scoring parameters While the preceding findings are generally consistent with the cardinal-inference hypothesis, they do not explicitly document reliance on cardinal information. The next part of our analysis fills that gap. On the assumption that Social Planners

[66]The hypothesized failure of Sen's α would suggest a corresponding failure of Arrow's Independence of Irrelevant Alternatives (IIA): if withholding information on the ranking of an unavailable option affects choice, then presumably changing its ranking will do likewise.

Table 7: Effects of removing alternatives

	(1)	(2)	(3)
	A. Baseline		
Profiles	A A B B B	A C C C B	A A B B C
	B C A A A	B B B B A	B B A C D
	C B C C C	C A A A C	C C C D A
			D D D A B
Choice distribution	A: 0.630, B: 0.365, C: 0.005	A: 0.012, B: 0.748, C: 0.240	A: 0.205, B: 0.694, C: 0.099, D: 0.002
	B. Option removed, rank information retained		
Profiles	A A B B B	~~A~~ C C C B	A A B B C
	B ~~C~~ A A A	B B B B ~~A~~	B B A C ~~D~~
	~~C~~ B ~~C~~ ~~C~~ ~~C~~	C ~~A~~ ~~A~~ ~~A~~ C	C C C ~~D~~ A
			~~D~~ ~~D~~ ~~D~~ A B
Choice distribution	A: 0.573, B: 0.427	B: 0.642, C: 0.358	A: 0.217, B: 0.674, C: 0.109
	C. Option and rank information removed		
Profiles	A A B B B	B C C C B	A A B B C
	B B A A A	C B B B C	B B A C A
			C C C A B
Choice distribution	A: 0.007, B: 0.993	B: 0.007, C: 0.993	A: 0.622, B: 0.368, C: 0.010
	D. p-values		
A vs. B	0.531	0.007	1.000
B vs. C	0.000	0.000	0.000
A vs. C	0.000	0.000	0.000

Notes: The profile in column 1 of Panel C is profile 14 of Table 1. In Panel A, the profile in column 3 is profile 18 from Table 3, and the profiles in the first and second columns are profiles 4 and 5 from Table 1, respectively. Columns 1 and 2 of Panel C both display the distribution of choices that subjects made for the single two-alternative profile they encountered. All decisions concern the work domain. p-values are based on two-sample Kolmogorov-Smirnov tests for equality of distributions.

are money-metric utilitarians, we use their stated beliefs about Stakeholders' reservation valuations for first-ranked, second-ranked, and third-ranked options to construct synthetic money-metric scoring parameters. We then ask whether the scoring parameters that rationalize actual choices are related to these synthetic utilitarian versions.

Formally, let $u_r^{i,d}$ denote Social Planner i's belief about the average Stakeholder's reservation valuation for his r-ranked alternative, for rank $r \in \{1, 2, 3\}$ and domain $d \in$\{work, politics\}.[67] The synthetic utilitarian scoring rule employs the score vector $[1, \tilde{s}_d, 0]$, where

$$\tilde{s}_d = \frac{u_2^{i,d} - u_3^{i,d}}{u_1^{i,d} - u_3^{i,d}}.$$

We examine the relation between the synthetic utilitarian scoring parameter $\tilde{s}$ and subjects' actual best-fitting scoring parameter s. In the work domain, we exclude 9 subjects who say they believe the average reservation wage is lower for the second-ranked option than for the first-ranked option, or lower for the third-ranked option than for the second-ranked option, on the grounds that they are likely inattentive or confused; in the political domain we drop 6 subjects. Thus, $\tilde{s}_d \in [0, 1]$. To avoid selection effects, we assign all subjects to their best-fitting scoring rules. We use OLS regression, using interval midpoints whenever best-fit scoring parameters are interval-identified. All regressions include fixed effects for preference profile presentation modes and for the order in which the subject made decisions about the work domain and the political domain.

The regression in Column 1 of Table 8 pools observations across the work and political domains. It includes a dummy variable for domain and clusters standard errors on the subject level. The coefficient of the synthetic scoring rule is positive and statistically significant. It remains positive when we run the regression separately for the two domains, but it is statistically significant only for the political domain. A potential explanation for this difference is that we measure the synthetic scoring parameter with less noise in the political domain because subjects are more familiar with political attitudes than with inclinations to perform various tasks, and consequently there is less attenuation of the coefficient.

Columns 4 to 6 add controls for Social Planners' risk attitudes and altruism, both measured as the percentile rank of the subject's average switching point for the two pertinent multiple decision lists. The coefficient of risk aversion is positive, as one would expect if Social Planners maximize the expected utility of a Stakeholder assessed behind a "veil of ignorance" concerning which Stakeholder has which ranking (in which case greater risk aversion implies greater concavity of the scoring rule), but the effect is weak. We also find that more altruistic Social Planners tend to use more concave scoring rules.

Next we ask whether the observed differences in scoring parameters across regimes is at least partially attributable to differences in cardinal inferences. In Column 7, we regress the difference between best-fit scoring rules across regimes for each subject on the corresponding difference between the synthetic scoring rules. The coefficient of interest remains positive and statistically significant. Indeed, this estimate closely resembles its counterparts in columns 1 and 4.

[67] We assume that the Social Planner's inferences about positional money-metric utility do not vary from one profile to another, and consequently elicit these beliefs only once.

Table 8: Relation between best-fitting scoring parameters and beliefs about reservation prices.

VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Lower and upper bound on estimated scoring parameter s						
Domain							
Work	✓	✓		✓	✓		✓
Politics	✓		✓	✓		✓	✓
Differenced (cross-domain)							✓
Scoring parameter $\tilde{s}$	0.168**	0.104	0.210**	0.147**	0.080	0.193*	0.137**
implied by beliefs	(0.067)	(0.076)	(0.104)	(0.067)	(0.077)	(0.106)	(0.069)
Risk aversion %-rank				0.063*	0.049	0.076	
				(0.033)	(0.034)	(0.047)	
Altruism %-rank				0.080**	0.065*	0.094*	
				(0.035)	(0.034)	(0.051)	
Political domain	-0.133***			-0.134***			
	(0.012)			(0.012)			
Observations	795	396	399	795	396	399	390
Subjects	405	396	399	405	396	399	390

Notes: Parameters estimated with OLS using midpoint values of best-fit score. All regressions control for the type of preference profile presentation and for whether the political domain was displayed before or after the work domain. Regressions include all subjects with monotonic beliefs about reservation prices. Regressions include subjects with multiple switches in the multiple decision lists used to elicit risk preferences and altruism. For these subjects we set the corresponding variable to the mean of the values among the other subjects, and we include two indicator variables for multiple switching points, one for each characteristic. Standard errors in columns 1 and 4 are clustered by subject.

Having shown that differences in cardinal inferences contribute to the observed differences in scoring rules across regimes, we now provide evidence that subjects also attach domain-independent weights to the various ordinal ranks. In other words, they appear to deploy a blend of cardinalism and ordinalism. In Column 1 of Table 9, we use an OLS regression to measure the subject-level correlation between synthetic scoring rules in the political domain and the work domain, conditional on presentation mode and order. While we acknowledge that these measures are noisy and that noise would attenuate the measured correlation, the absence of any correlation suggests that the true cardinal inferences are unrelated across regimes. In Column 2, we use a similar regression to measure the (conditional) subject-level correlation between best-fit scoring rules in the two domains. It is positive and highly significant despite the apparent absence of any correlation in cardinal inferences. Thus, best-fit scoring rules appear to reflect some common factor that is unrelated to cardinal inferences.

Table 9: Relation between synthetic and best-fitting scoring parameters across domains.

VARIABLES	(1) Scoring parameter in political domain Synthetic	(2) Best-fitting
Scoring parameter in work domain		
Synthetic	-0.074	
	(0.058)	
Best-fitting		0.638***
		(0.064)
Observations	390	390
R^2	0.012	0.261

Notes: OLS regressions. Both equations control for the type of preference profile presentation and for whether the political domain was displayed before or after the work domain. Regressions include all subjects with monotonic beliefs about reservation prices.

5 General population samples

In this section, we ask whether our main conclusions extend to general population samples. We also test whether the general public in countries with divergent social and political traditions, the United States and Sweden (Alesina and Glaeser, 2004), use similar or divergent criteria when aggregating ordinal preferences, and we explore external validity by asking whether ordinal aggregation criteria among the general public are related to attitudes toward political processes. Our cross-cultural comparison can potentially help explain why different nations gravitate toward different types of policies. As Alesina and Angeletos (2005) point out, policies may diverge either because different cultures have fundamentally different preferences, or because of beliefs, historical accidents, institutions, and/or equilibrium selection.

In these supplemental experiments, each social choice entails the allocation of $20 (in the U.S.) or SEK170 (in Sweden) to one of four charities: Doctors without Borders, Unicef, Oxfam, and the International Fund for Animal Welfare.[68] These organizations are well known in both countries and represent diverse causes that have broad appeal across the political spectrum. We recruited 712 Swedish and 805 U.S. voting-age citizens through Dynata and Lucid to serve as Social Planners. Each Social Planner aggregates the preferences of same-country Stakeholders, recruited through pollfish. All Social Planners see the same reduced set of profiles we used for the political domain in our main experiment, as well as either the actual profile for a group of Stakeholders or a randomly generated profile. Social Planners know that one of the preference profiles they consider corresponds to real Stakeholders with 10% probability. We use abridged instructions that carefully explain the preference

[68] At the time of the study, these amounts were roughly equivalent according to market exchange rates ($1 $\approx$ SEK 8.50).

displays (see Appendix E.2). Subjects must pass an abbreviated comprehension check to participate.[69] See Appendix D for additional implementation details and demographic summary statistics.

To make our samples more representative of the respective general populations, we weight observations as follows. For the US sample, we use the 2018 General Social Survey (Smith et al., 2019) to generate weights for 16 population categories defined by (i) gender (male, female), (ii) race (white, black, hispanic, other), and (iii) political party preference (Democrat, Republican). For the Swedish sample, we use data from Statistics Sweden (2018) to generate weights for 12 categories defined by (i) gender, and (ii) political party preference (Left Party, Social Democratic Party, Green Party, Centre Party, Moderate Party, Sweden Democrats).[70]

Because these data require us to categorize subjects based on seven three-option profiles rather than seventeen, it is important to bear in mind the following limitations. First, categorizations based on fewer choices are more sensitive to one or two noisy selections. Second, because it is harder to detect irresoluteness with fewer profiles when using only consequential choices, certain scoring rules such as Borda are more difficult to distinguish from neighboring rules. Third, some rules become entirely indistinguishable. In particular, the Condorcet rule, plurality rule, and plurality runoff all have the same implications for the reduced set of three-option profiles. In light of the first two issues, we rely on seven-profile classifications mainly to make comparisons across subject pools. The distributions themselves should be taken with a grain of salt, as there are systematic differences between the seven- and seventeen-profile classifications for our student population in the work domain.

In light of the third issue, we begin by discussing the four-option class-separating profiles, which cleanly differentiate between proper scoring rules, Condorcet rules, and plurality runoff, as in Section 4.4 (recall Table 3). Only 8.0% of U.S. subjects and 5.8% of Swedish subjects consistently choose the Condorcet winner for both Condorcet-separating profiles. Moreover, 24.4% (U.S.) and 14.6% (Sweden) of those subjects express indifference between options for at least one of these profiles, which suggests that they follow plurality rule. That leaves roughly 5% to 6% of subjects in the Condorcet category. Likewise, small minorities (3.1% of US subjects and 1.7% of Swedish subjects) choose the plurality runoff winner in both runoff-separating profiles. All of these results closely parallel our findings for the student sample.

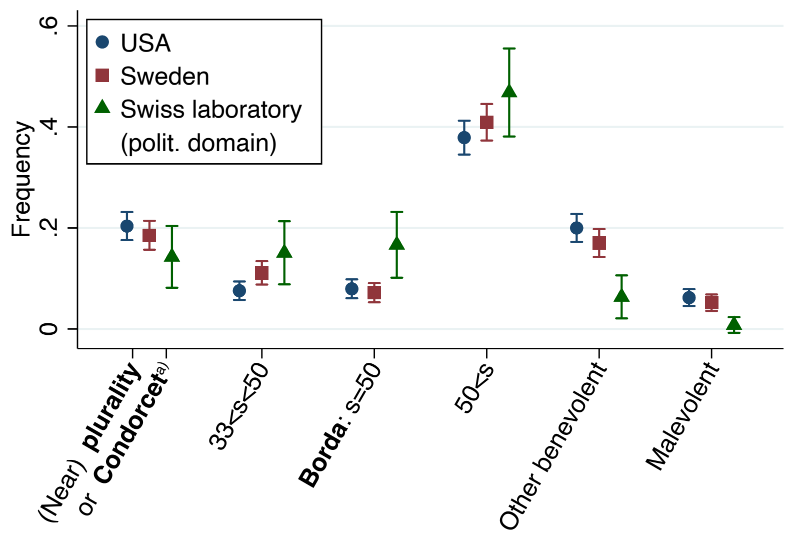
Next, using the Bayes classifier, we assign each subject to the best-fitting rule based on their consequential choices for the seven three-option profiles. Figure 10 displays the results. To facilitate comparisons across samples, we consolidate several categories (strictly concave scoring rules, all benevolent alternatives aside from scoring rules, and all malevolent rules). The figure shows classification frequencies for the U.S. sample, the Swedish sample, and the Swiss student sample (political domain). When comparing the results for the student sample to either of the general population samples, one

[69] Subjects recruited through Dynata could proceed in spite of failing the comprehension check. We exclude such observations from our data.

[70] For both countries, these are the most recent data that include the requisite information for each combination of characteristics.

should bear in mind that the domains are similar but not identical. Because we have found that aggregation rules vary somewhat across domains (Section 4.5), we would not expect the classifications to match perfectly.

Figure 10: Classification of general population samples to pre-specified rules



Notes: Bayes classifications based on consequential choices for the seven three-option preferences profiles indicated with stars in Table 1. General population observations weighted to make the samples representative with respect to gender, party preference, and race (US only).

Differences in classification frequencies between the Swedish and U.S. general population samples are remarkably small and statistically insignificant. Hence, the fundamental aggregation preferences of U.S. and Swedish citizens are extremely similar, which suggests that they do not contribute to policy divergences. The general population distributions also resemble the distribution for the student sample despite the difference in domains.[71] Like the low prevalence of Condorcet rules (noted above), the popularity of strictly concave scoring rules proves to be a robust phenomenon. Notably, the elevated frequencies of "Other benevolent rules" are attributable primarily to the antiplurality runoff rule, which is closely related to the strictly concave alternatives. The modestly higher frequencies of malevolent rules suggest that our general population samples may include slightly higher fractions of subjects who did not take the tasks seriously. Similarly, the slightly elevated use of plurality rule, the least cognitively demanding alternative, could be attributable to greater laziness.

Finally, we ask whether our measures of aggregation preference correlate with self-reported attitudes toward political processes. Our survey presents subjects with two hypothetical candidates for

[71] As expected, the Borda rule appears to be less popular when we classify fewer subjects based on seven profiles rather than seventeen. When we also employ the indifference data to classify subjects based on seven profiles, Borda frequencies increase substantially.

political leadership of the nation. It describes Candidate 1 as polarizing: "*Most citizens either love him or hate him. There is hardly anyone who does not have a strong opinion. If candidate 1 were elected, some citizens would be exhilarated, many others would be devastated, and nobody would be indifferent.*" We describe Candidate 2 as a compromise alternative: "*While he is nobody's greatest favorite, most citizens would be ok with candidate 2. If he were elected, nobody would be exhilarated, nobody would be devastated.*"[72] We ask subjects "*Which candidate better represents the will of the citizens of the nation?*" In addition, subjects indicate their level of agreement or disagreement with each of the following two statements: "*The political system should strive for compromise solutions that everyone can live with even if the result is nobody's absolute favorite,*" and "*What the majority wants is right for a country, even if that makes some citizens suffer.*" We construct an index of preference for compromise policies as follows: we assign values 0, $\frac{1}{3}$, $\frac{2}{3}$, and 1 to the responses 'strongly disagree', 'disagree', 'agree', and 'strongly agree' for the first of these two questions, invert the scores for the second, and average responses across them.

Table 10: Relation between behavioral measures of preference for compromise and self-reports

VARIABLES	(1) Prefers compromise candidate	(2)	(3) Prefers compromise solutions	(4)
Mean of the dep. var.	0.801		0.686	
Scoring parameter	0.077*	0.070*	0.035	0.022
	(0.042)	(0.042)	(0.056)	(0.055)
Demographic controls		✓		✓
Subjects	1,404	1,404	1,404	1,404

Notes: OLS regressions. All regressions control for sample provider and display fixed effects. Demographic controls include nationality, gender, age, marital status, percentile rank of respondents' education within the sample in their respective country, indicators for being unemployed and for being part-time employed, as well as the percentile rank of income within the sample for the respondents' country.

Table 10 examines the relation between these self-reported attitudes and our behavioral measure of aggregation preference. For Columns 1 and 2, the dependent variable is a binary indicator of the preference for the compromise candidate; in Columns 3 and 4, it is our measure of preference for compromise policies. Each column reports an OLS regression pooling over U.S. and Swedish subjects. The main independent variable is the subject's scoring parameter, which we compute by restricting the Bayes classification to scoring rules and assigning interval midpoints. In all cases, we control for sample provider and display fixed effects. While the results are not strong, they are nevertheless suggestive. As expected, those who deploy more concave scoring rules tend to prefer

[72]We randomize the order of the descriptions as well as the candidate labels.

greater compromise in political processes. The relationship is significant at the 10% level in Columns 1 and 2, and statistically insignificant but directionally consistent in Columns 3 and 4.[73]

6 Conclusion

Our objective in this paper has been to understand the judgments people make when they aggregate others' ordinal preferences. We find that the overwhelming majority of subjects behave as if they rely on *scoring rules*. The Borda and antiplurality rules are the most common alternatives, and a sizeable majority of subjects uses strictly concave scoring rules, indicating a pronounced preference for compromise over majoritarian solutions. Plurality rule, Condorcet rules, supermajority, unanimity, and various runoff rules are relatively rare. The classification's fit is excellent, and clustering analysis reveals no major omissions from our list of pre-specified rules. We find systematic and significant differences in the distributions of rules between the work domain and the political domain, but these differences are of limited magnitude. Because our classifications are highly predictive of choices out of sample, including across domains, we infer that ordinal aggregation also entails stable structural elements. While subjects act as if they attach substantial domain-independent weight to the various ordinal ranks, we also find strong indications that subjects aggregate ordinal preferences based in part on inferences about cardinal utility, thus deploying a blend of cardinalism and ordinalism. Supplemental experiments show that the distributions of aggregation preferences in the U.S. and Sweden, countries with divergent political and social traditions, are remarkably similar, and both resemble the distribution for the student sample used in our main experiment. Even so, there is suggestive evidence that the use of more concave scoring rules in experimental decisions correlates with a preference for electing compromise candidates.

Our analysis suggests many potential directions of inquiry for future work. The mere fact that people rely to some degree on cardinal inferences when presented with ordinal information, and treat money as a cardinal index when presented with monetary payoffs, does not imply that they are money-metric welfarists. In the spirit of Roberts (1980), it would be useful to understand which types of cardinal comparisons people find meaningful, and which (if any) they find arbitrary. Do they ignore ordinal information when cardinal information is available, or do they use both? Are money-metric measures of well-being compelling when consequences are non-monetary? Another potential line of inquiry would investigate the relationships between preferences over rules revealed by choices over outcomes, preferences over rules revealed by choices over rules (as in Engelmann and Grüner, 2017; Hoffmann and Renes, 2017; Engelmann et al., 2020), and preferences over rules implied by approval of axioms (in the spirit of Nielsen and Rehbeck, 2020 and others). It would also be of interest to investigate how awareness of manipulability influences rule selection.

[73] Ambuehl et al. (2021b) offer corroborative evidence for external validity: German elected representatives of more centrist political parties use more concave scoring rules.

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ONLINE APPENDIX

Interpreting the Will of the People
A Positive Analysis of Ordinal Preference Aggregation

Sandro Ambuehl, B. Douglas Bernheim

Table of Contents

A Additional design and implementation information **1**

A.1 Excluded three-option profiles . . . 1

A.2 Distance between rules on profiles used the in political domain . . . 3

A.3 Implementation details . . . 4

B Bayesian Classifier **5**

B.1 Derivation of the Bayesian posterior . . . 5

B.2 Monte Carlo Simulations . . . 6

C Supplementary results **10**

C.1 Effects of preference displays . . . 10

C.2 Classifications by fit . . . 12

C.3 Last-place aversion . . . 13

D General population samples: Supplementary information **14**

D.1 Implementation details . . . 14

D.2 Respondent summary statistics . . . 14

E Experiment instructions **16**

E.1 Main experiment . . . 16

E.2 General population experiment . . . 53

E.3 Elicitation of mTurk worker Stakeholder preferences . . . 65

E.4 Elicitation of Swiss citizen Stakeholder preferences . . . 75

References **76**

A Additional design and implementation information

A.1 Excluded three-option profiles

Given anonymity and neutrality, our setting of five Stakeholders and three alternatives allows for 42 different preference profiles. The work domain in our experiment uses the 17 profiles that provide the largest amount of discrimination between our pre-specified rules. Table A.1 lists the remaining 25 profiles that are not included in our experiment. These omitted profiles cannot expand the set of scoring rules, scoring runoffs, or q-majority rules we can distinguish. In the case of scoring rules and q-majority rules, this can be shown analytically. For the case of scoring runoff rules, we show this point using brute-force computer scripts.

Figure A.1 shows that these profiles would also provide little or no additional ability to distinguish between our pre-specified rules.

Table A.1: Excluded three-alternative profiles.

A	A	B	B	B	A	A	A	A	A	A	A	B	B	B	A	B	B	B	B	A	C	B	B	B
B	C	C	C	C	B	B	B	B	B	B	C	C	C	A	B	C	A	A	A	B	B	C	A	A
C	B	A	A	A	C	C	C	C	C	C	B	A	A	C	C	A	C	C	C	C	A	A	C	C
A	C	C	C	C	A	A	A	A	A	A	A	B	B	B	A	B	B	B	B	A	A	A	B	B
B	A	B	B	B	B	B	C	C	C	B	C	C	A	A	B	A	A	A	A	B	C	C	A	A
C	B	A	A	A	C	C	B	B	B	C	B	A	C	C	C	C	C	C	C	C	B	B	C	C
A	C	B	B	B	A	A	B	B	B	A	C	C	C	C	A	C	C	B	B	A	C	B	B	B
B	A	C	C	C	B	B	C	C	C	B	A	A	A	B	B	B	B	C	C	B	B	A	A	A
C	B	A	A	A	C	C	A	A	A	C	B	B	B	A	C	A	A	A	A	C	A	C	C	C
A	C	B	B	B	A	A	B	B	B	A	C	C	C	C	A	C	C	B	B	A	A	A	C	C
B	A	C	C	A	B	B	A	A	A	B	A	A	B	B	B	B	B	C	A	B	C	C	A	A
C	B	A	A	C	C	C	C	C	C	C	B	B	A	A	C	A	A	A	C	C	B	B	B	B
A	C	B	B	B	A	A	A	A	A	A	B	B	B	B	A	B	B	B	B	A	B	B	B	B
B	A	C	A	A	B	C	C	C	C	B	C	C	C	C	B	C	C	A	A	B	C	C	C	A
C	B	A	C	C	C	B	B	B	B	C	A	A	A	A	C	A	A	C	C	C	A	A	A	C

Notes: Most our pre-specified rules make the same prediction about which option will be chosen for most of the profiles in this table. Note that for the majority of these profiles, the preference rank distributions of the alternatives are fully ordered by stochastic dominance, *and* the option with the lowest (least preferred) rank distribution is statewise dominated by another option.

Figure A.1: Distance between rules used in the political domain.

	Scoring, $s=0$	Scoring, $0<s<\frac{1}{3}$	Scoring, $s=\frac{1}{3}$	Scoring, $\frac{1}{3}<s<\frac{1}{2}$	Scoring, $s=\frac{1}{2}$	Scoring, $\frac{1}{2}<s<\frac{3}{5}$	Scoring, $s=\frac{3}{5}$	Scoring, $\frac{3}{5}<s<\frac{2}{3}$	Scoring, $s=\frac{2}{3}$	Scoring, $\frac{2}{3}<s<\frac{3}{4}$	Scoring, $s=\frac{3}{4}$	Scoring, $\frac{3}{4}<s<\frac{4}{5}$	Scoring, $s=\frac{4}{5}$	Scoring, $\frac{4}{5}<s<1$	Scoring, $s=1$	Runoff, $0\leq s\leq\frac{1}{3}$	Runoff, $\frac{1}{3}<s<\frac{1}{2}$	Runoff, $\frac{1}{2}<s<1$	Runoff, $s=1$	Condorcet	Supermajority	Unanimity
Scoring, $s=0$	0	2	2	2	2	2	2	2	2	2	2	2	2	2	11	2	2	2	23	2	12	22
Scoring, $0<s<\frac{1}{3}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=\frac{1}{3}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $\frac{1}{3}<s<\frac{1}{2}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=\frac{1}{2}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $\frac{1}{2}<s<\frac{3}{5}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=\frac{3}{5}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $\frac{3}{5}<s<\frac{2}{3}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=\frac{2}{3}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $\frac{2}{3}<s<\frac{3}{4}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=\frac{3}{4}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $\frac{3}{4}<s<\frac{4}{5}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=\frac{4}{5}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $\frac{4}{5}<s<1$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Scoring, $s=1$	11	9	9	9	9	9	9	9	9	9	9	9	9	9	0	9	9	9	16	9	16	21
Runoff, $0\leq s\leq\frac{1}{3}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Runoff, $\frac{1}{3}<s<\frac{1}{2}$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Runoff, $\frac{1}{2}<s<1$	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Runoff, $s=1$	23	25	25	25	25	25	25	25	25	25	25	25	25	25	16	25	25	25	0	25	25	19
Condorcet	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	25	0	12	22
Supermajority	12	12	12	12	12	12	12	12	12	12	12	12	12	12	16	12	12	12	25	12	0	14
Unanimity	22	22	22	22	22	22	22	22	22	22	22	22	22	22	21	22	22	22	19	22	14	0

Notes: This graph plots the set of 22 benevolent rules on both the horizontal and vertical axes. Each cell reports the number of profiles (out of the 25 profiles omitted from the experiment) for which a given pair of rules differ from each other. We use the definition that two rules differ on a profile if they select a different subset of options (distance = 1); otherwise they do not differ on that profile (distance = 0).

A.2 Distance between rules on profiles used the in political domain

Figure A.2 displays the distance between any pair of our pre-specified rules on the preference profiles we use for the political domain. Entries of zero off the diagonal indicate that the corresponding pair of rules cannot be separately identified using either of our methods. Moreover, using incentivized choice alone, we cannot separately identify any pair of rules that differ from each other on only a single profile if the set of options chosen by one rule on that profile is a subset of those chosen by the other rule.

Figure A.2: Distance between rules used in the political domain.

	Scoring, $s=0$	Scoring, $0<s<\frac{1}{3}$	Scoring, $s=\frac{1}{3}$	Scoring, $\frac{1}{3}<s<\frac{1}{2}$	Scoring, $s=\frac{1}{2}$	Scoring, $\frac{1}{2}<s<\frac{3}{5}$	Scoring, $s=\frac{3}{5}$	Scoring, $\frac{3}{5}<s<\frac{2}{3}$	Scoring, $s=\frac{2}{3}$	Scoring, $\frac{2}{3}<s<\frac{3}{4}$	Scoring, $s=\frac{3}{4}$	Scoring, $\frac{3}{4}<s<\frac{4}{5}$	Scoring, $s=\frac{4}{5}$	Scoring, $\frac{4}{5}<s<1$	Scoring, $s=1$	Runoff, $0\leq s\leq\frac{1}{3}$	Runoff, $\frac{1}{3}<s<\frac{1}{2}$	Runoff, $\frac{1}{2}<s<1$	Runoff, $s=1$	Condorcet	Supermajority	Unanimity
Scoring, $s=0$	0	0	1	1	3	3	4	4	5	5	6	6	7	7	7	0	0	0	7	0	6	7
Scoring, $0<s<\frac{1}{3}$	0	0	1	1	3	3	4	4	5	5	6	6	7	7	7	0	0	0	7	0	6	7
Scoring, $s=\frac{1}{3}$	1	1	0	1	3	3	4	4	5	5	6	6	7	7	7	1	1	1	6	1	6	6
Scoring, $\frac{1}{3}<s<\frac{1}{2}$	1	1	1	0	2	2	3	3	4	4	5	5	6	6	6	1	1	1	7	1	6	7
Scoring, $s=\frac{1}{2}$	3	3	3	2	0	2	3	3	4	4	5	5	6	6	6	3	3	3	5	3	6	6
Scoring, $\frac{1}{2}<s<\frac{3}{5}$	3	3	3	2	2	0	1	1	2	2	3	3	4	4	4	3	3	3	7	3	6	7
Scoring, $s=\frac{3}{5}$	4	4	4	3	3	1	0	1	2	2	3	3	4	4	4	4	4	4	6	4	6	7
Scoring, $\frac{3}{5}<s<\frac{2}{3}$	4	4	4	3	3	1	1	0	1	1	2	2	3	3	3	4	4	4	7	4	6	7
Scoring, $s=\frac{2}{3}$	5	5	5	4	4	2	2	1	0	1	2	2	3	3	3	5	5	5	6	5	6	7
Scoring, $\frac{2}{3}<s<\frac{3}{4}$	5	5	5	4	4	2	2	1	1	0	1	1	2	2	2	5	5	5	7	5	6	7
Scoring, $s=\frac{3}{4}$	6	6	6	5	5	3	3	2	2	1	0	1	2	2	2	6	6	6	6	6	6	7
Scoring, $\frac{3}{4}<s<\frac{4}{5}$	6	6	6	5	5	3	3	2	2	1	1	0	1	1	1	6	6	6	7	6	6	7
Scoring, $s=\frac{4}{5}$	7	7	7	6	6	4	4	3	3	2	2	1	0	1	1	7	7	7	6	7	7	7
Scoring, $\frac{4}{5}<s<1$	7	7	7	6	6	4	4	3	3	2	2	1	1	0	0	7	7	7	7	7	7	7
Scoring, $s=1$	7	7	7	6	6	4	4	3	3	2	2	1	1	0	0	7	7	7	7	7	7	7
Runoff, $0\leq s\leq\frac{1}{3}$	0	0	1	1	3	3	4	4	5	5	6	6	7	7	7	0	0	0	7	0	6	7
Runoff, $\frac{1}{3}<s<\frac{1}{2}$	0	0	1	1	3	3	4	4	5	5	6	6	7	7	7	0	0	0	7	0	6	7
Runoff, $\frac{1}{2}<s<1$	0	0	1	1	3	3	4	4	5	5	6	6	7	7	7	0	0	0	7	0	6	7
Runoff, $s=1$	7	7	6	7	5	7	6	7	6	7	6	7	6	7	7	7	7	7	0	7	7	5
Condorcet	0	0	1	1	3	3	4	4	5	5	6	6	7	7	7	0	0	0	7	0	6	7
Supermajority	6	6	6	6	6	6	6	6	6	6	6	6	7	7	7	6	6	6	7	6	0	3
Unanimity	7	7	6	7	6	7	7	7	7	7	7	7	7	7	7	7	7	7	5	7	3	0

Notes: This graph plots the set of 22 benevolent rules on both the horizontal and vertical axes. Each cell reports the number of profiles (out of the 7 used in the political domain) for which a given pair of rules differ from each other. We use the definition that two rules differ on a profile if they select a different subset of options (distance = 1); otherwise they do not differ on that profile (distance = 0).

A.3 Implementation details

Table A.2 shows session details. The same three research personnel led each session, checked student IDs and citizenship, and were available for questions over zoom during the entire session.

Table A.2: Session times and participation

Date	Time	Number of participants
01/18/2021	13:30-15:00	17
01/19/2021	13:30-15:00	43
01/19/2021	15:30-17:00	41
01/20/2021	13:30-15:00	45
01/20/2021	15:30-17:00	31
01/21/2021	13:30-15:00	45
01/21/2021	15:30-17:00	40
01/25/2021	13:30-15:00	46
01/25/2021	15:30-17:00	44
01/26/2021	13:30-15:00	20
01/26/2021	15:30-17:00	33

B Bayesian Classifier

B.1 Derivation of the Bayesian posterior

Here, we derive the explicit expression for the Bayesian posteriors, $P(R, \epsilon|c)$, that our Bayesian classifier maximizes. For each preference profile t, a social choice rule R prescribes a subset $S^t_R \subseteq \{A, B, C\}$ of admissible options. For each t, the subject makes a choice $c_t \in \{A, B, C\}$. If the individual follows rule R with error probability ϵ and behaves according to the assumptions listed in Section 4.2, then the probability of choosing each alternative is given by the following expressions for $X, Y, Z \in \{A, B, C\}$ with X, Y, and Z mutually distinct from each other.

$$\begin{aligned}
P\big(c_t = X|S^t_R = \{X\}; \epsilon\big) &= 1 - \frac{2}{3}\epsilon \\
P\big(c_t = Y|S^t_R = \{X\}; \epsilon\big) &= \frac{1}{3}\epsilon \\
P\big(c_t = X|S^t_R = \{X, Y\}; \epsilon\big) &= \frac{1}{2} - \frac{1}{6}\epsilon \\
P\big(c_t = Z|S^t_R = \{X, Y\}; \epsilon\big) &= \frac{1}{3}\epsilon \\
P\big(c_t = X|S^t_R = \{A, B, C\}; \epsilon\big) &= \frac{1}{3}
\end{aligned}$$

Moreover, by the assumption of conditional independence across rounds, the probability of observing choice sequence $c = (c_1, \ldots, c_T)$ from a subject who follows rule R is given by $P(c|R) = \prod_{t=1}^{T} P\big(c_t|S^t_R\big)$. Given the assumption of uniform prior probabilities across rules and error probabilities, we derive the prior probability of observing choice sequence c as $P(c) = \sum_R \frac{1}{N_R} \int_0^1 P(c|R; \epsilon)d\epsilon$, where N_R is the total number of rules. By Bayes' rule, the posterior associated with rule R and error probability ϵ conditional on the sequence of choices c is thus given by

$$P(R, \epsilon|c) = \frac{P(c|R; \epsilon)\mu_i}{P(c)}. \tag{1}$$

B.2 Monte Carlo Simulations

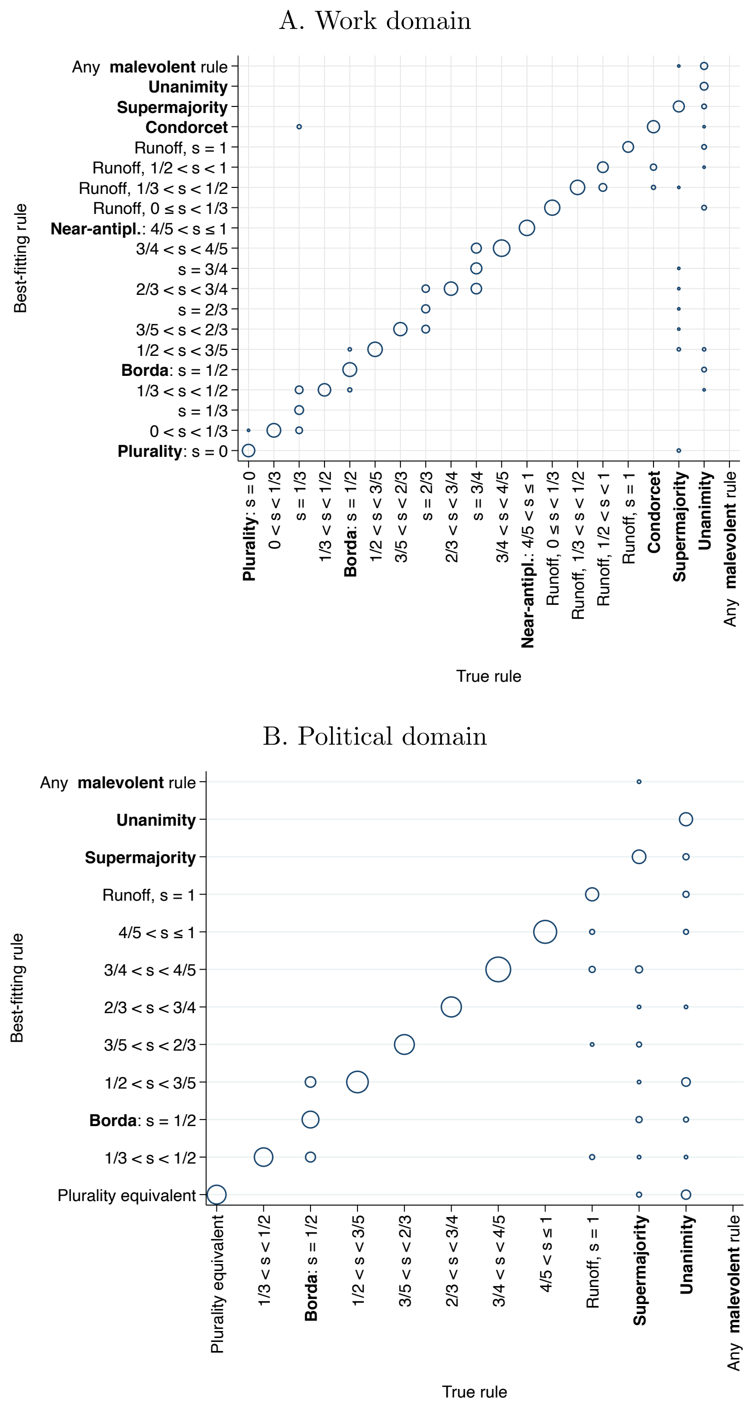
We use Monte Carlo simulations to test (i) whether the Bayesian classifier reliably detects the use of pre-specified rules, and (ii) whether noise introduces bias.

To answer the first question, we simulate a sample of 1,000 subjects. We uniformly randomly assign each simulated subject to one of the identifiable benevolent rules in each domain. Each simulated subject follows the assigned rule exactly and randomizes uniformly among all tied options in case of irresoluteness. We then run the Bayesian classifier on this sample of simulated subjects, both using all three-option profiles available in the work domain, and using the three-option profiles available in the political domain. Figure B.3 shows the results. Using the profiles available in the work domain (Panel A), three features stand out. First, the data are generally tightly centered around the diagonal. Second, subjects following a massively irresolute rule (supermajority and unanimity) are frequently confused for following another rule. Yet, even in these cases, the rule generating the choices receives non-trivial weight. Hence if the classifier assigns zero weight to these two rules, it is unlikely that any subject actually followed one of these rules. Third, while scoring rules with a parameter between the boundaries of identifiable intervals are correctly classified in all cases, scoring rules with a parameter on the interval boundaries are sometimes confused for those with a parameter just above or just below the interval boundary. The reason is mechanical. In case of a scoring parameter on the interval boundary (henceforth: a point-identified scoring rule), the set of chosen options is the union of the options chosen by the neighboring interval-identified scoring rules. By assumption, subjects uniformly randomize in case of ties. If a point-identified scoring rule is irresolute on two profiles, and the neighboring interval-identified scoring rules are resolute on those profiles, for instance, there is a 50% chance that the randomization over the ties happens to coincide exactly with the choices prescribed by one of the neighboring interval-identified scoring rules. Panel B performs the same exercise but restricts the available data to the profiles available in the political domain and the set of rules to the rules identifiable in that domain. Qualitatively, we observe the same results as in the work domain, with the exception that the (rather irresolute) antiplurality-runoff rule is sometimes confused with other rules.

To answer the second question, we simulate 4,000 subjects who choose uniformly randomly from all options in each round. We then run the Bayesian classifier on this sample of simulated subjects, both using all three-option profiles available in the work domain, and using the three-option profiles available in the political domain. Figure B.4 shows the resulting distribution of best-fitting types. Panel A uses the profiles available in the work domain. Unsurprisingly, close to half of simulated subjects are assigned to a malevolent rule.[74] Within the set of benevolent rules, we see that the least resolute rules, supermajority and unanimity, attract by far the largest fraction of subjects. The remaining rules all attract similar numbers of subjects, between one and roughly five percent.

[74] Because our selection of profiles is not random, deviations from 50% are expected.

Figure B.3: Bayesian classifier if rules are followed exactly



Notes: Each of 1,000 simulated subjects is randomly uniformly assigned one identifiable benevolent rule in the respective domain and follows the rule exactly. In case of ties, simulated subjects randomize uniformly among all tied options. We run the Bayesian classifier on the simulated data. Fractions of subjects are indicated by the sizes of circles.

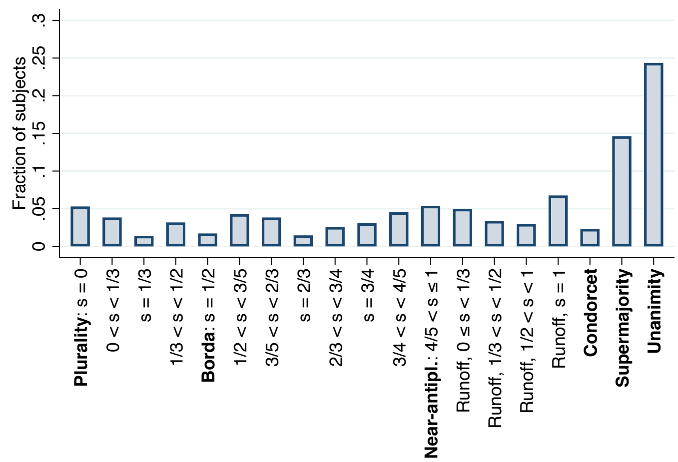
Notably, neither of the modes we observe in our experimental data, Borda and near-antiplurality, attract a disproportionate fraction of randomly generated subjects.

Panel B uses the set of profiles available in the political domain. We find that 40.8% of simulated subjects are classified as malevolent. Among the remainder, we observe the same tendency as in the work domain to assign randomly generated subjects to the least resolute rules, and no tendency to disproportionately assign subjects to Borda or near-antiplurality.

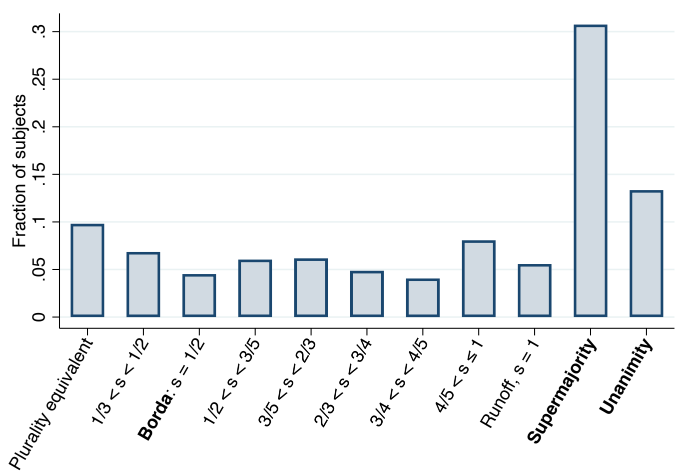
Overall, we conclude that our classification results in Section 4.2.2 are not an artifact of classifying noisy data.

Figure B.4: Bayesian classifier on uniformly random noise

A. Work domain
(50.4% classified as malevolent)



B. Political domain
(40.8% classified as malevolent)



[a)] The category "Consistent with $0 \leq s < 33$" includes scoring rules with $0 \leq s < \frac{1}{3}$, any Condorcet extension, and any scoring runoff rule with $s < 1$."

Notes: Each of 4,000 simulated subjects makes uniformly random choices from all three options. We run the Bayesian classifier on the simulated data. Graphs display the distribution over benevolent rules only.

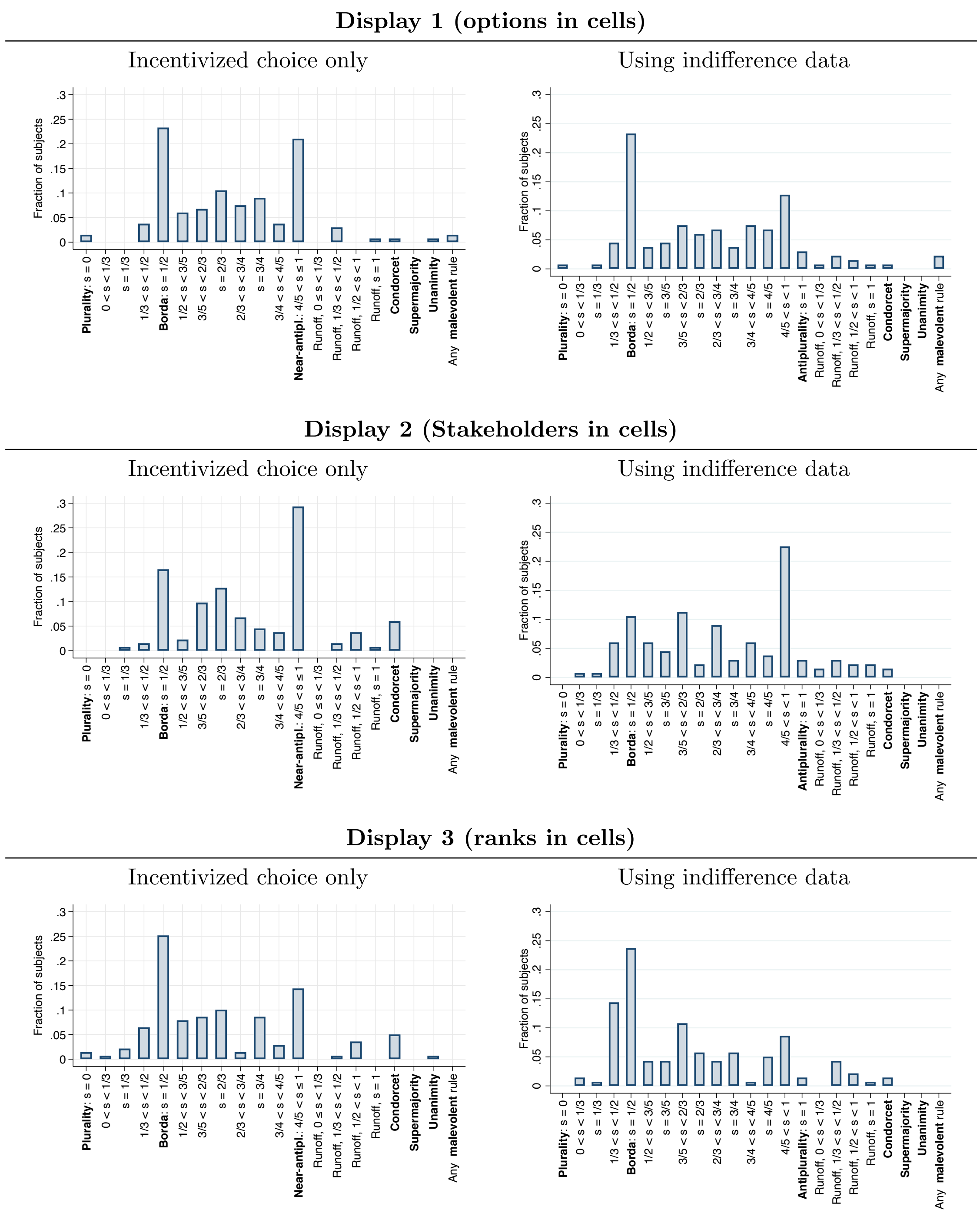
C Supplementary results

C.1 Effects of preference displays

Here, we study the influence of the format in which we presented preference profiles on our classification results. Figure C.5 displays the classification to pre-specified rules separately by display format. Graphs on the left hand side use incentivized choices only while those on the right hand side make use of indifference statements.

In each case we see that (i) malevolent and qualified majority rules receive vanishing support, (ii) runoff rules receive minor support, and (iii) the vast majority of subjects follow a concave scoring rule. Differences across the graphs mainly concern the modes of Borda and near-antiplurality. Relying on incentivized data alone, both of these rules emerge as the modal choices in each display version. While Borda is the more pronounced mode in display versions 1 and 3, near-antiplurality is the more pronounced mode in display version 2. This same pattern emerges to a larger extent if we incorporate indifference data for classification. Overall we conclude that our main results are robust to the preference display used, except that we cannot reliably distinguish whether Borda or near-antiplurality is the more pronounced mode.

Figure C.5: Best fitting pre-specified rules, work domain, by display



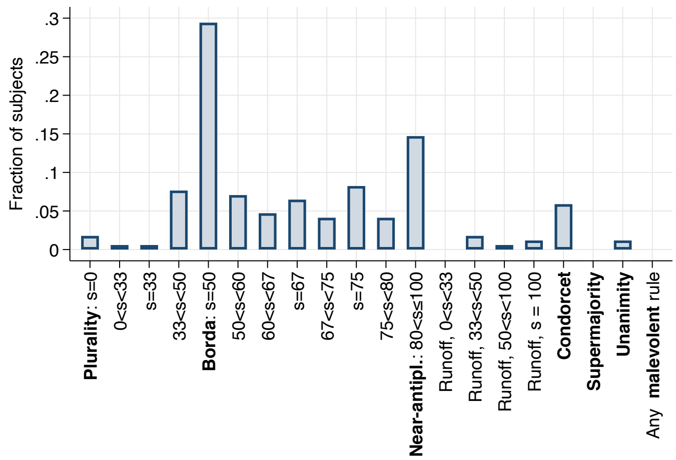
Notes: Displays 1, 2, and 3 are shown in Figures 3, 4, and 5, respectively.

C.2 Classifications by fit

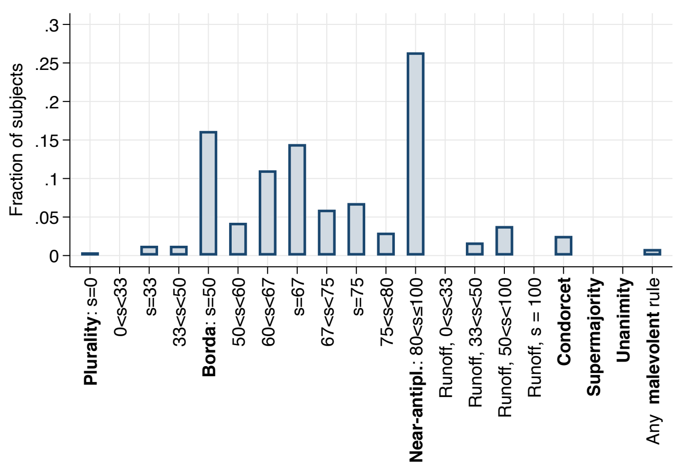
Panel A of Figure C.6 displays the results of our classification based on incentivized choice separately for subjects whose choices are perfectly consistent with their best-fitting rule and those whose choices deviate on at least one preference profile from their best-fitting rule.

Figure C.6: Best fitting pre-specified rules, by perfect fit

A. Subjects with perfect fit to the assigned rule



B. Subjects with imperfect fit to the assigned rule



Notes: Results of the classification based on incentivized data alone. Panel A shows the subset of subjects whose choices are a perfect fit to the best-fitting rule. Panel B shows the subset of subjects who fit the best-fitting rule imperfectly.

C.3 Last-place aversion

Does the the concave aggregation we document in section 4.2 simply represent linear aggregation with a discount for receiving one's least-preferred alternative (last-place aversion; formalized as using scoring vectors that assign score $\frac{k-1}{K-1}$ to any option ranked $k \geq 2$, but score $-d < 0$ to the option ranked last in the case of K alternatives), or does it reflect globally concave aggregation in the sense that subjects' choices are described by score vectors that are strictly concave across all ranks (for instance by instance, by using scoring vectors that assign score $\left(\frac{k-1}{K-1}\right)^{\gamma}$ to the option ranked k in the case of K alternatives)? Choices in the runoff-separating profiles of Table 3 show that globally concave aggregation plays a substantial role. In these profiles, the choice of option A is consistent with a scoring rule with $s \leq 0.5$ whereas the choice of B or C is consistent with $s \in [\frac{1}{2}, \frac{2}{3}]$ and $s \in [\frac{2}{3}, 1]$, respectively, where $s = (\frac{1}{2})^{\gamma}$. Importantly, in these profiles, option B is ranked last by one individual, and option A is ranked last by two individuals. In the three-option profiles 3 and 4, 64% of subjects choose the option consistent with a weakly concave scoring rule. If last-place aversion explains this choice pattern, then, in the four-option profiles 22 and 23, we should observe that at least 64% of subjects avoid the last-place-generating options (A or B). In contrast, the fraction of subjects selecting either option A or option B is given by 64.2% and 81.7% for the first and second runoff-separating profiles, respectively. Hence, last-place aversion cannot be the sole reason for the choice patterns we observe in the three-option profiles.

D General population samples: Supplementary information

D.1 Implementation details

Instructions are abridged versions from the laboratory experiment, but include the detailed presentation of the preference display. We only use versions 1 and 2 of presenting preference profiles (see Figures 3 and 4, respectively), since version 3 is often perceived as less intuitive.

A native speaker of Swedish at a commercial translation agency translated the survey into Swedish. We aimed for 1000 respondents in each country. We began sampling with Dynata until no further subjects could be recruited. We then continued sampling the same survey with Lucid until no further subjects could be recruited (potential repeat participants were automatically filtered out by the Qualtrics survey). We retain subjects who participated through Dynata if they correctly answered the comprehension check about the preference display. For subjects recruited through Lucid we added a filter such that subjects could complete the survey only if they correctly answered these comprehension check questions. Because of these requirements, which are more stringent than typical for the subject population, we managed to obtain 712 subjects in Sweden and a comparable 805 subjects in the US. We recruited all Stakeholders with pollfish.

D.2 Respondent summary statistics

Table D.3 presents the distribution of the demographic characteristics of the general population samples.

Table D.3: Demographic characteristics of the general population samples.

Variable	USA	Sweden
Gender		
Male	0.509	0.560
Female	0.489	0.433
Non-binary	0.001	0.007
Age		
18-25	0.098	0.184
26-35	0.088	0.188
36-45	0.062	0.141
46-55	0.155	0.179
56-65	0.160	0.191
66-75	0.200	0.100
76-85	0.214	0.015
>85	0.022	0.001
Race		
White (non-hispanic)	0.625	
Black	0.057	
White (hispanic)	0.255	
Other	0.063	
Native Swedish		0.778
Other European background		0.124
Other		0.098
Political party preference		
Republican or other right-learning party	0.477	
Democrat or other left-learning party	0.523	
Left Party		0.149
Social Democratic Party		0.249
Green Party		0.065
Centre Party		0.089
Moderate Party		0.239
Sweden Democrats		0.210
Education		
Primary school	0.000	0.052
Some high school	0.005	0.058
High school or GED	0.145	0.266
Some college	0.194	0.159
Associate's or Bachelor's degree	0.419	0.412
Master's degree	0.189	0.030
Doctoral degree	0.048	0.024
Income bracket		
< USD 50k, < SEK 500k	0.420	0.779
between USD 50k and 100k or SEK 500k and 1,000k	0.349	0.208
> USD 100k, > SEK 1,000k	0.231	0.013
Marital status		
Married	0.511	0.370
Widowed	0.097	0.038
Divorced	0.142	0.090
Separated	0.010	0.032
Never married	0.241	0.470
N	805.000	711.000

E Experiment instructions

E.1 Main experiment

Technical Check

To test whether your computer can display the study correctly, please copy the following number into the field below

225784

← →

WELCOME

This is a research study run by the Department of Economics at the University of Zurich.

This study will take about **50 to 80 minutes** to complete. The average participant will earn Fr. 45 for completing this study. This consists of a base payment of Fr. 30 that you will receive with certainty, and a variable payment of up to Fr. 38 that depends on your decisions and on luck.

You will receive payment in cash at the end of this study.

This study has been approved by the ethics review board of the department of economics in protocol OEC IRB # 2020-035. The study is run in collaboration with Stanford University. It has been approved in Stanford IRB protocol #53339.

By clicking the "continue" button below, you consent to participating in this decision making study.

→

Instructions

Please read the instructions carefully.

There will be two comprehension checks. You will be able to continue with the study only if you correctly answer all questions in both comprehension checks.

This study has three parts.

In **part A**, you will make decisions that determine what type of work a group of five other study participants will have to complete.

In **part B**, you will make decisions that determine which of five political parties will receive a donation of CHF30

In **part C**, you will make decisions that determine your own payoff.

Consequences of your decisions in parts A and B

There is a one in four chance that your choices will determine either the work that the group of five other study participants will complete or the party that will receive the donation. If so, each of your decisions in parts A and B is equally likely to count. Only one decision will be carried out.

Consequences of your decisions in part C

Your compensation for completing this study consists of a fixed payment of Fr. 30 and a variable payment ranging between Fr. 0 and Fr. 38; on average your total payment will be around Fr. 45. The variable payment will be determined by part C of the study. It will depend on your decisions and on luck.

If you are matched to a group of five other participants, you are the only person who is matched to them.

On behalf of the Economics Department at UZH, we guarantee that we carry out all aspects of the study exactly as we describe to you. The rules governing our research do not permit us to deceive our participants in any way.

Part A

← →

Who will be affected by my decisions?

In this part of the study, you will make decisions that may affect a group of five other participants. These five other participants are workers whom we have recruited on the crowdsourcing website Amazon Mechanical Turk (MTurk).

Please read the following description about MTurk and workers on that platform, so you know who will be affected by the decisions you make in this study today.

amazon mechanicalturk

About workers on MTurk

Amazon Mechanical Turk is a website on which businesses can hire remotely located workers.

Employers post jobs known as Human Intelligence Tasks (HITs), such as identifying specific content in an image or video, writing product descriptions, or answering questions, among others. Workers browse among existing jobs and complete them in exchange for a rate set by the employer.

Any resident of the United States can register as a worker on MTurk. Once registered they complete tasks in exchange for money. Payment for completed tasks can be transferred to a Worker's U.S. bank account.

Workers set their own hours and are not under any obligation to accept any particular task. They are entirely flexible regarding how many hours they work, when they work, or where they do it. In this sense, they face similar opportunities as individuals who drive for the rideshare platform Uber.com.

← →

The MTurk workers recruited for this experiment

All workers who may be affected by your decisions have been active on mTurk for a substantial amount of time. They all have completed at least 1000 Human Interaction Tasks, and they have received good reviews for their work (at least 98% satisfaction rate). All of them are based in the United States.

Pay for workers in this study, and in the United States in general

You are deciding for mTurk workers whom we will remunerate with an average payment of USD 15 per hour. That amount is similar to the average earnings of US-drivers on the rideshare platform Uber. Drivers earn USD 14.73 per hour, after expenses such as car insurance and repairs, according to www.ridester.com/how-much-do-uber-drivers-make/. Taxi drivers in Zurich, by comparison, earn around CHF 22 per hour.

A similar relation holds for cashiers. While a cashier at the Swiss retailer Migros earns about CHF 20 per hour, the large US retailers Walmart and Target remunerate typical cashiers with USD 10 and USD 13 per hour, respectively.

A reasonable rule of thumb is that USD1 buys a bit less than one-and-a half times as much in the United States as CHF 1 buys in Zurich. At the same time, many workers in the United States also earn substantially less than the average resident of Zurich.

← →

Your decisions

As explained before, we have enlisted a team of five workers from MTurk. We have hired the five workers to complete five different work tasks that we will explain momentarily.

Your task in this study is to decide which of the five workers will complete which task.

Important

The five workers have already participated in a first part of the study. They will complete the second part of the study after you have made your choice about which worker will complete which task. You are the only person who determines the tasks of those five workers.

← →

The five workers' tasks

The team of five workers will need to complete a total of five different tasks.

Not all workers will prefer the same tasks. Tasks that are attractive to some will be unattractive to others, and vice versa.

The tasks include, for instance, audio transcription, sorting hate-speech out of a dataset of online comments, or classifying movie reviews. Some tasks may be emotionally charged, some may require a lot of concentration and careful thought, and others simply require some time and practice. We will show you each task momentarily.

Each team-member will receive $10 once they have completed the task assigned to them. If a team-member fails to complete the assigned task, they will not receive any payment.

On the next five pages, you'll see each of the five tasks. Please complete one or two examples of each task, then click continue.

← →

Movie Review Classification (task 1)

In this task, the worker will classify 400 movie reviews by whether they are positive or negative; that is, by whether the reviewer liked or disliked the movie. This task will take **around half an hour**, but could take 15 minutes more or less depending on the worker's motivation and speed.

Reviews that have been classified into positive or negative by hand are an important input for training computer algorithms.

Please give it a try!
Once you're done, click the next button. It will appear as soon as you have classified one review correctly. (Scroll to the bottom of the page.)

Reviews classified correctly: 0

This movie is excellent. I found it very interesting. I thought the Mendigo legend was pretty cool. The acting was also great, as well as the costumes, production, photography, directing and script.

A very happy family, on vacation gets stranded in the middle of nowhere after they hit a deer. A huntsman then appears and is very angry and outraged over the fact that one of the deer's antler's is broken. He then starts to stalk the family and weird things start to happen to them.

See this movie. It's worth it. Kudos to the cast, crew and filmmakers. Two Thumbs Way Up!

POSITIVE NEGATIVE

←

Spoken Words Transcription (task 2)

In this task, the worker will hear 400 spoken words. For each of them, the worker will click a button to indicate what was said. Workers with experience in audio-transcription will typically require **about 15 minutes** to transcribe the text, whereas workers with less experience may take a bit longer. Transcribing spoken words takes few special skills, but requires a quiet environment and good headphones or speakers.

Transcribing spoken text is needed as computers can readily analyze written data, but often have trouble with spoken words.

Please give it a try!
Once you're done, click the next button. It will appear as soon as you've transcribed one word correctly. (Scroll to the bottom of the page.)

Words transcribed correctly: 0

-0:01

BED CAT DOG DOWN GO HAPPY
HOUSE SEVEN UP YES

←

Image Labeling (task 3)

In this task, the worker will see a sequence of 400 images. For each image the worker will click a button to indicate the content of the image. This task will take **about half an hour** but could take 15 minutes more or less depending on the worker's speed. Labeling images does not take any special skills, and can easily be done while listening to music.

Images whose content has been indicated by hand are an important input for training computer algorithms (see, e.g., https://en.wikipedia.org/wiki/Labeled_data).

Please give it a try!
Once you're done, click the next button. It will appear as soon as you have classified one image correctly. (Scroll to the bottom of the page.)

Images labeled correctly: 0

Plane Car
Cat Bird
Deer Dog
Frog Ship
Horse Truck

Twitter hate speech sorting (task 4)

In this task, the worker will sort 400 short messages posted on twitter.com by whether they include hate speech (e.g. racist or sexist statements). This task will take **around half an hour,** but could take 15 minutes more or less depending on the worker's motivation and speed.

Some workers may find this task emotionally taxing.

Messages that have been hand-classified into offensive and harmless are an important input for training computer algorithms to automatically detect offensive messages (see, e.g., https://en.wikipedia.org/wiki/Labeled_data).

Please give it a try!
Once you're done, click the next button. It will appear as soon as you've classified one message correctly. (Scroll to the bottom of the page.)

Classified correctly: 0

HOWDYDOWdY11
@HowdyDowdy11

I just finished running 2.27 km in 13m:25s with #Endomondo #endorphins https://t.co/et8hp3BI9G

HATE SPEECH | CLEAN

Assigning apprentices to mentors (task 5)

This task requires a bit more thought than the others. The worker assigned to this task will repeatedly assign each of five (hypothetical) apprentices at a (hypothetical) company to one of five (hypothetical) mentors at that company.

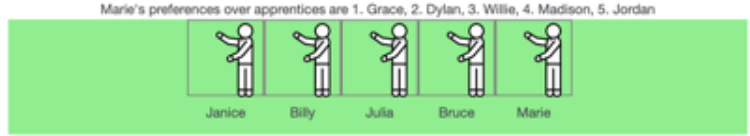
The worker will have to create such assignments for 5 companies. This task will take **around half an hour,** but could take 15 minutes more or less.

The reason is that worker cannot just create any arbitrary assignment. Instead, each of the apprentices have indicated which mentor they would prefer most, second most, and so on. Likewise, each of the mentors have indicated which of the apprentices they would most like to mentor, which they would second-most like to mentor, and so on. The worker will need to find a way to pair apprentices and mentors to make all apprentices and mentors as happy as possible. (Specifically, the worker will have to find an assignment in which there are no two people that are not paired with each other, but would prefer each other over their assigned partners.)

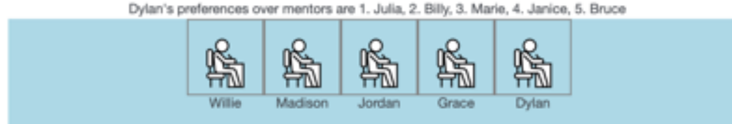
Some people will find this task more engaging than the less challenging tasks, while others will be put off by it. Some people will be much better at this task than others.

Give this task a try if you like. (You do not need to complete it.) Scroll to the bottom and click Next once you're done.

Mentors
Janice's preferences over apprentices are 1. Dylan, 2. Grace, 3. Willie, 4. Madison, 5. Jordan
Billy's preferences over apprentices are 1. Dylan, 2. Grace, 3. Willie, 4. Madison, 5. Jordan
Julia's preferences over apprentices are 1. Dylan, 2. Willie, 3. Madison, 4. Jordan, 5. Grace
Bruce's preferences over apprentices are 1. Jordan, 2. Dylan, 3. Madison, 4. Grace, 5. Willie
Marie's preferences over apprentices are 1. Grace, 2. Dylan, 3. Willie, 4. Madison, 5. Jordan



Apprentices
Willie's preferences over mentors are 1. Bruce, 2. Billy, 3. Julia, 4. Janice, 5. Marie
Madison's preferences over mentors are 1. Bruce, 2. Janice, 3. Julia, 4. Billy, 5. Marie
Jordan's preferences over mentors are 1. Janice, 2. Julia, 3. Billy, 4. Bruce, 5. Marie
Grace's preferences over mentors are 1. Bruce, 2. Marie, 3. Billy, 4. Janice, 5. Julia
Dylan's preferences over mentors are 1. Julia, 2. Billy, 3. Marie, 4. Janice, 5. Bruce



Pair mentors and apprentices

Drag and dropping them into the boxes below.

CHECK ANSWER

How will I assign tasks to workers?

Part A of this study has 28 rounds. In each round, you will select an "Assignment," by which we mean a way of allocating the five tasks among the five workers. We will present you with two to four possible Assignments. Your task will be to select one of the Assignments.

One of these rounds pertains to the five workers we have assigned to you. Your choice of an Assignment for that round is real, and we will actually carry it out (if this part of the experiment has randomly been chosen to be carried out). Your choice in that round will determine which worker will complete which task. However, we are not going to tell you which round involves your real choice.

You should therefore treat every one of these rounds as if it were real, because it could be!

← →

The pre-selected assignments

Recall that a task assignment simply describes which worker will complete which task. We will refer to each Assignment by an icon like , , or . These icons have absolutely no meaning, apart from serving as labels to help you visually distinguish between the assignments.

Here's an example (don't bother to remember it, it's just an example)

	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5
Assignment	Image labeling	Speech transcription	Hate-speech filtering	Apprentice-mentor assignment	Movie review classification
Assignment	Apprentice-mentor assignment	Movie review classification	Image labeling	Hate-speech filtering	Speech transcription

With Assignment , worker 1 will label images, worker 2 will transcribe speech, and so on, as you can see in the first row of the table.

With Assignment , on the other hand, worker 1 completes the apprentice-mentorship assignment, worker 2 classifies movie reviews, and so forth, as you can see in the second row of the table.

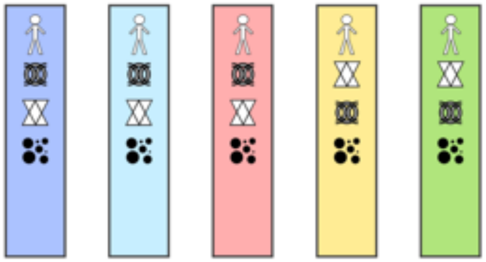
One more thing: As in the example above, if you switch from one Assignment to another, then *every* worker will complete a different task. There are no two Assignments in which some worker completes the same task in each of those Assignments.

← →

The workers' preferences

The five workers differ in which tasks they like or dislike.

To help you make your decision, you will see each group member's preferences over the pre-selected Assignments as in the following picture. Each bar (with a stick figure) represents one member of the group of five for whom you are choosing an Assignment.



In this picture, each bar (with a stick figure) represents one worker. Each bar contains all three symbols , , and , that represent the three possible task assignments from which you will get to choose. In each bar, the Assignment on top is the one that the team member prefers most, whereas the Assignment on the bottom is the one he or she prefers least.

Consider the worker on the very left (dark blue), for instance. Of the three tasks he might complete, he most prefers the one he will be given in Assignment . (As you can see in the table below, that would be Task D). His second-most preferred task is the one he will complete in Assignment ; and he least prefers the task he will complete in Assignment . The worker on the very right (green) has different preferences. She most prefers the task she would be given in Assignment , second-most the task she'll get with Assignment , and she least prefers the task she'll have to complete in Assignment .

Important: *You will only learn the workers' preferences over the pre-selected Assignments. You will not learn who will complete which task in which Assignment.*

	Worker 1	Worker 2	Worker 3	Worker 4	Worker 5
Assignment	Task B	Task A	Task D	Task E	Task C
Assignment	Task A	Task D	Task C	Task B	Task E
Assignment	Task E	Task B	Task A	Task C	Task D

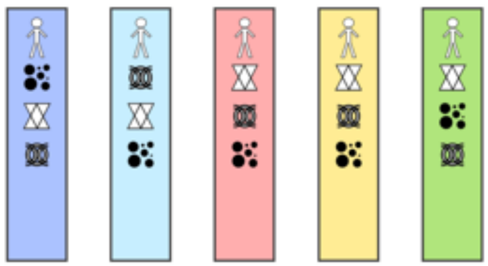
← →

Comprehension Check 1

To make sure you correctly understand how information about the Workers' preferences is being displayed to you, please answer the questions below. All questions refer to the Assignments below. (These are *different* Assignments than on the previous page. The workers' preference rankings are different, too.)

If you have trouble finding the correct answers, please click the "previous" button below (with the arrow to the left) and study the instructions more carefully.

If you feel you have understood the instructions, but you still cannot continue, please send an email to sandro.ambuehl@econ.uzh.ch



How many workers rank assignment on top (most preferred)?

0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○

How many workers rank assignment in the middle?

0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○

How many workers rank assignment on the bottom (least preferred)?

0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○

Which Assignment does the worker on the very left prefer most?

Assignment ○ Assignment ○ Assignment ○

Which Assignment does the worker on the very left prefer neither most nor least (middle)?

Assignment ○ Assignment ○ Assignment ○

Which Assignment does the worker on the very left prefer least?

Assignment ○ Assignment ○ Assignment ○

Where does the worker on the very right rank Assignment ?

Top ○ Middle ○ Bottom ○

Where does the worker on the very right rank Assignment ?

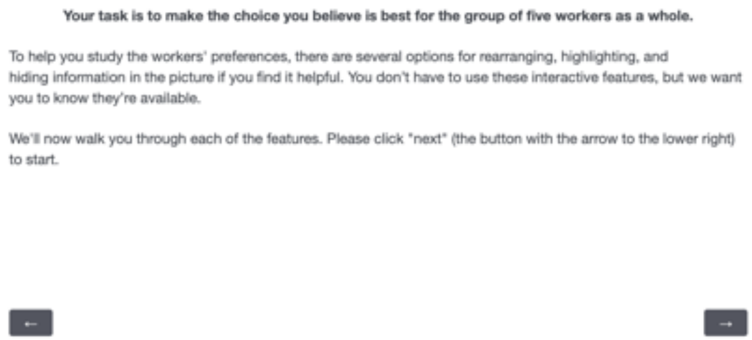
Top ○ Middle ○ Bottom ○

Where does the worker on the very right rank Assignment ?

Top ○ Middle ○ Bottom ○

One of your answers to the comprehension check questions is incorrect. Please study the image with the preferences carefully. You might also want to double-check the instructions to make sure you understand them.

Close



Subjects see each of the following statements, and complete the requested action before the next statement is shown.

(i) You can drag and drop each worker to a different position. Please give this a try by dragging a worker to a different location.

(ii) Underneath each stick figure representing the worker, you will see a button labeled ”Hide”. If you click it, that worker's preferences will be hidden. If you click it a second time, that worker's preferences will be displayed again. Please hide, then show, one of the workers.

(iii) At the bottom of the figure, you see two rows of buttons. Buttons in the first row allow you to highlight an assignment. If you click the button a second time, the highlighting will be switched off. Please give this a try.

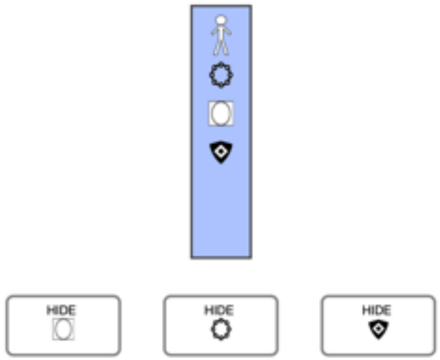
(iv) Buttons in the second row allow you to hide an assignments. If you click such a button a second time, the assignment will be displayed again. Please hide, then show one of the assignments.

(v) Finally, on top of the figure, you see a button labelled “shuffle”. That button will shuffle the order of the workers. Please click it.

(vi) Great, that's all the features. Please click “next” to continue.

Hiding Assignments changes the figure. Why and how?

The figure will only show you the Workers' preferences over the options that you are currently displaying. If the figure shows all three Assignments, you will see them stacked in three rows. If you hide one of the Assignments, then you will see the Workers' preferences over the two remaining assignments, so there will only be two rows. For instance, consider the Worker below.



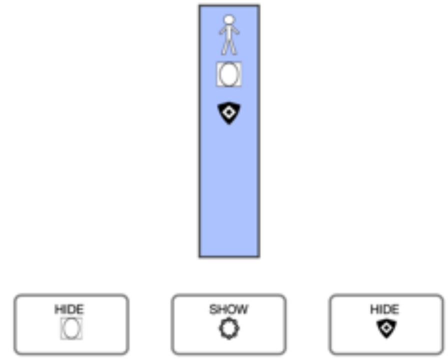
Now, go ahead and hide Assignment .

←

→

Hiding Assignments changes the figure. Why and how?

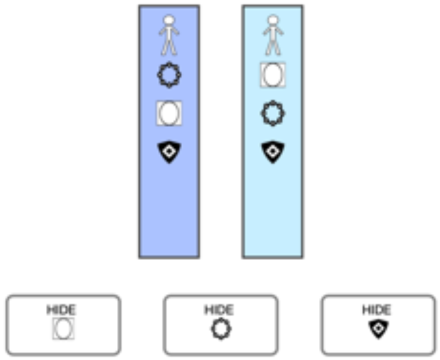
The figure will only show you the Workers' preferences over the options that you are currently displaying. If the figure shows all three Assignments, you will see them stacked in three rows. If you hide one of the Assignments, then you will see the Workers' preferences over the two remaining assignments, so there will only be two rows. For instance, consider the Worker below.



Now, go ahead and hide Assignment .

Assignment is the one the Worker prefers most out of the three Assignments. Once we hide Assignment , there are only two Assignments left. Hence, the figure only shows two rows of Assignments. Out of the two Assignments that are still being displayed, the Worker prefers Assignment most, so that's now placed into the top row. But note that if you display all three options, he would rank that Assignment only in the middle; he likes the non-displayed Assignment better than Assignment !

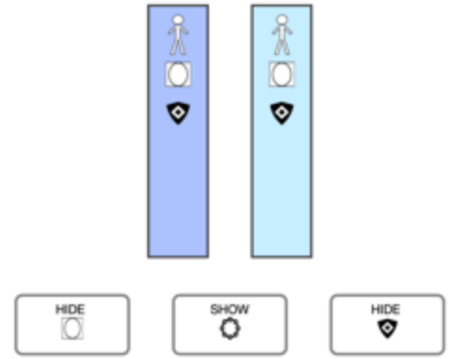
Now, let's look at what happens if there is more than one worker; let's add a second Worker. You can see that Worker's preference ranking over the Assignments below. In this figure, the two workers have different preferences for Assignment ; for one Worker it's the best of the three, but for the other Worker its only the second-best of the three:



Now, again, hide Assignment .

←   →

Now, let's look at what happens if there is more than one worker; let's add a second Worker. You can see that Worker's preference ranking over the Assignments below. In this figure, the two workers have different preferences for Assignment ; for one Worker it's the best of the three, but for the other Worker its only the second-best of the three:



Now, again, hide Assignment .

As you can see, Assignment is now in the top row for both workers. Why did that happen? The reason is that both Workers like Assignment more than Assignment . How the workers would rank Assignment compared to the hidden option is not visible from this figure (but you can see it by displaying Assignment again).

←   →

Information about the group members' preferences

The group members have already participated in a first part of the experiment, in which they told us their true preference ranking over the tasks.

They have done that for the options in exactly one of the 28 rounds you will see. Your decision for that round *will* be carried out for the group.

We are not going to tell you which of the 28 rounds presents you with your real choice.

Hence, you should make each decision in each round as if it is the one that counts, because it might be!

Click here if you would like to know more about how the group member's preferences were measured.

(Otherwise, scroll down all the way)

In the first part of the study, each worker first saw the same description of each task that you have seen before. Then, each worker sorted the five tasks in the order of their preference.

To make sure workers reported their genuine preferences, each worker faced a 5% chance that their own choice would determine which task they would have to complete. Workers also knew that with the remaining chance, a different procedure would determine the task they will complete (but workers did not learn what that procedure is).

(To make sure workers reported their entire preference ranking genuinely, rather than only their top choice, workers knew that the computer had randomly chosen two tasks in advance. Of those two tasks, they would complete the one they had ranked more highly. Workers did not know which two tasks the computer had pre-selected. Accordingly, it was in the worker's own best interest to truthfully report their preference ranking over all five tasks.)

You are deciding for a group of workers in which *none* of the workers themselves determined the outcome.

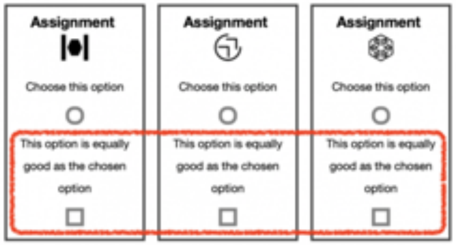
← →

What if several Assignments are equally good for the group of five workers?

In some rounds, there might be multiple Assignments that you deem equally good for the group. In other rounds, there might be one single Assignment that you deem best for the group.

In all rounds, you will have to choose one single Assignment to be carried out.

We will ask you, however, whether there are other alternatives you deem equally good as the one you have chosen, like this:



Please answer those questions truthfully.

The block of text below the button is shown only to subjects who click the button.

What happens if a worker is assigned a task, but does not to complete it?

A worker who does not complete the assigned task will not receive the $10 they would otherwise have received.

Moreover, we will check that each worker completes each task successfully. If not, we will treat them as if they didn't complete the task.

Do the five workers know each other?

No, they do not. We have recruited them at random from a pool of many thousand workers on the Amazon Mechanical Turk online labor platform.

← →

How will my own payment be determined?

We have been discussing Part A of the study. Your choices in Part A may affect other people, but they will not affect your own payment. Your payment will be determined by one of the choices you will make in Part C of the study. We will explain how once Part C begins.

Please pay attention throughout and make all decisions carefully.
Your choices will have real consequences for a group of five other participants (if this part is randomly selected to be carried out)! The other participants are real people.

← →

Comprehension Check

Before you start with your decisions, please check all the correct statements below (and only those).

If you have trouble finding the correct answers, please click the "previous" button below (with the arrow to the left) and study the instructions more carefully.

If you feel you have understood the instructions, but you still cannot continue, please raise your hand.

- [ ] The five workers are real. My choice of Assignment will determine the task each group member will complete (if this part is randomly chosen to be carried out).
- [ ] The five workers are hypothetical, there are no real people affected by my decisions.
- [ ] Exactly one round is the "real" one: My decision in that round will determine the work that each of the members of a group of five workers on Amazon Mechanical Turk will complete (if this part is randomly chosen to be carried out).
- [ ] The five workers have already participated in a first part of the experiment in which they revealed their preferences over the tasks.
- [ ] A worker who is assigned to a task can just click through without paying any attention. The quality of work is irrelevant; the worker will receive the $10 in any case
- [ ] A Worker will receive $10 for completing the assigned task.
- [ ] Two of the rounds will determine the work that each of the five workers will have to complete (if this part is randomly chosen to be carried out).
- [ ] Each worker will complete the same task, regardless of what I choose.
- [ ] The five tasks are: hate speech filtering, image labeling, audio transcription, assigning apprentices to mentors, and classifying movie reviews.

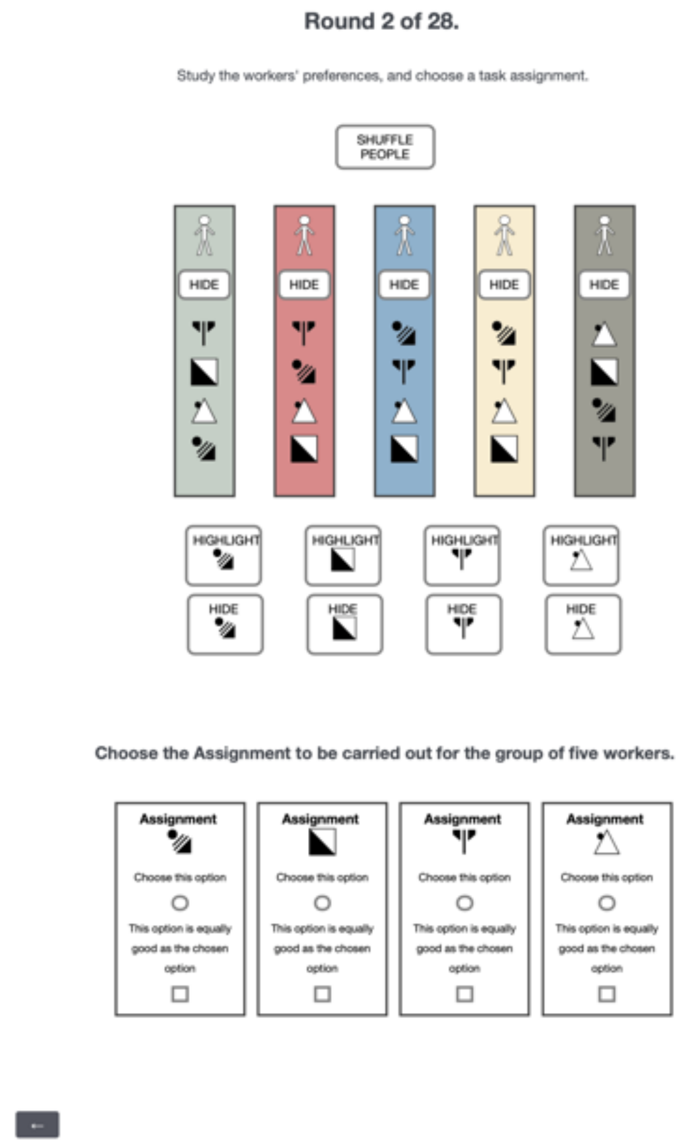
←　　→

Your decisions begin now.

Please make each decision as if it is the one that counts, because it might be!

→

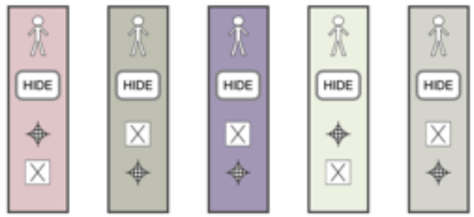

Round 1 of 28.
Study the workers' preferences, and choose a task assignment.
SHUFFLE WORKERS
HIDE
HIGHLIGHT
HIDE
Choose the Assignment to be carried out for the group of five workers.
Assignment
Choose this option
This option is equally good as the chosen option


Round 2 of 28.
Study the workers' preferences, and choose a task assignment.
SHUFFLE PEOPLE
HIDE
HIGHLIGHT
HIDE
Choose the Assignment to be carried out for the group of five workers.
Assignment
Choose this option
This option is equally good as the chosen option

Round 8 of 28.

Study the workers' preferences, and choose a task assignment.

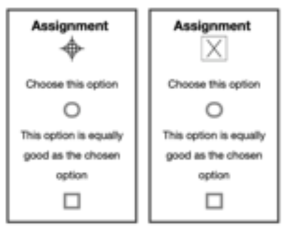
SHUFFLE WORKERS



HIGHLIGHT HIGHLIGHT

HIDE HIDE

Choose the Assignment to be carried out for the group of five workers.



Unavailable Assignments

In each of the next three rounds, one of the Assignments will be unavailable. These rounds proceed like all the other rounds, except that you will not be able to choose the unavailable Assignment.

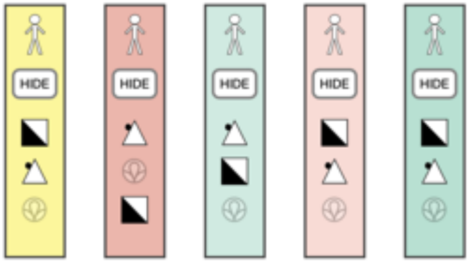
← →

Round 25 of 28.

Study the workers' preferences, and choose a task assignment.

In this round, Assignment is unavailable. You will not be able to select that Assignment.

SHUFFLE WORKERS



HIGHLIGHT | HIGHLIGHT | HIGHLIGHT

HIDE | HIDE | HIDE

Choose the Assignment to be carried out for the group of five workers.

Assignment	Assignment	Assignment
Option unavailable	Choose this option	Choose this option
	This option is equally good as the chosen option	This option is equally good as the chosen option

Part B

→

A Fr. 30 donation to a political party

In this part of the study, you will make decisions about a Fr. 30 donation to one of the five political parties that have the largest representation in the Swiss National Council. These are the following parties:

- FDP Die Liberalen FDP / PLR (FDP.The Liberals)
- SVP UDC SVP / UDC (Swiss People's Party)
- SP SP / PS (Social Democratic Party)
- CVP CVP / PDC (Christian Democratic People's Party)
- GRÜNE LES VERTS GPS / Verts (Green Party)

← →

Your decisions

We have enlisted five Swiss citizens (who are eligible to vote in Switzerland) to participate in a first part of this study. Each of the five citizens ranked the five political parties according to how much or how little he or she likes the respective party to receive the donation of Fr. 30. The donation will go to exactly one of the five parties. You cannot split up the donation.

Your task in this study is to decide to select one of the five political parties based on the preferences of the five citizens assigned to you.

Important

The five Swiss citizens assigned to you are not assigned to any other study participant. Hence, you are the only person who decides based on the preferences of these five citizens.

← →

Here's how you will make your decision.

In each round of this part, we will present you with three or four parties which are randomly selected from the five largest political parties in Switzerland. In each round, you will choose a party based on the preferences of the five citizens you are seeing in that round.

Important:
We ask you to choose a party based on the group as a whole, taking into account their preferences and disagreements, but ignoring your own political attitudes

That's why we anonymize the parties. We will not refer to the them by their names but by abstract symbols like , , or . Each symbol represents the donation going to a specific party. For instance, symbol  might indicate that the donation goes to the SVP / UDC, symbol  might indicate that the donation goes to the SP / PS, etc. (Don't bother to remember these symbols, they are just examples. They have absolutely no meaning, apart from serving as labels to help you visually distinguish between the parties).

Moreover, the way we recruited the citizens makes it impossible for you to tell which symbol stands for which party based on the citizens' preferences."

Here's how we did that.

We have recruited a total of 249 Swiss citizens, of which 5 may be assigned to you. We have asked each citizen to rate themselves as left, center, or right. We have collected the sample of 249 citizens such that we have exactly 83 who rate themselves as right, 83 who rate themselves as center, and 83 who rate themselves as left. The 5 citizens assigned to you are randomly drawn from these 249 citizens.

← →

How will I decide which party receives the donation?

Part B of this study has 12 rounds. One of these rounds pertains to the five Swiss citizens we have assigned to you. Your choice of a party for that round is real, and we will actually carry it out (if this part of the study is randomly chosen to be carried out). Your choice in that round will determine which political party will receive the donation of Fr. 30. However, we are not going to tell you which round involves your real choice.

You should therefore treat every one of these rounds as if it were real, because it could be!

← →

Comprehension Check

Before you start with your decisions, please check all the correct statements below (and only those).

If you have trouble finding the correct answers, please click the "previous" button below (with the arrow to the left) and study the instructions more carefully.

If you feel you have understood the instructions, but you still cannot continue, please raise your hand.

- [ ] Exactly one round is the "real" one: My decision in that round will determine which political party will receive the donation of Fr. 30 (if this part of the study is randomly chosen to be carried out)
- [ ] Each political party will receive the same amount of money, regardless of what I choose (if this part of the study is randomly chosen to be carried out).
- [ ] The five Swiss citizens are real. My choice of a political party based on their preferences will determine which political party will receive a donation (if this part of the study is randomly chosen to be carried out).
- [ ] If one of my decisions from this part is carried out, one of the five largest Swiss political parties will receive a donation of Fr. 30.
- [ ] The five Swiss citizens have already participated in a first part of the experiment in which they ranked the five biggest Swiss political parties according to how much / how little they would like them to receive the donation of Fr. 30.
- [ ] The five largest Swiss political parties that the five Swiss citizens have ranked are: SVP, FDP, SP, Gruene, CVP (now known as Die Mitte)
- [ ] Two of the rounds will determine which political party will receive the donation (if this part of the study is randomly chosen to be carried out).
- [ ] The five Swiss citizens are hypothetical, and no donation will actually be made to a political party.

← →

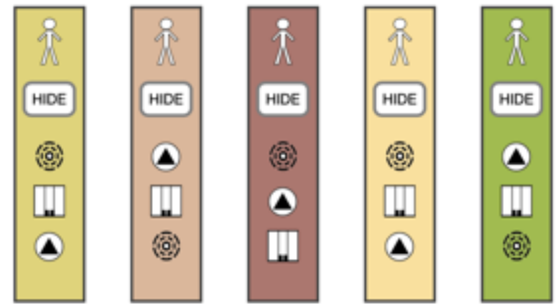
Round 1 of 12 about the donation to a political party.

CVP SP SVP UDC GRÜNE LES VERTS FDP Die Liberalen

Study the Swiss citizens' preferences, and choose a party based on the preferences of this group of citizens as a whole.

(For this round, the computer has randomly chosen 3 of the five political parties)

SHUFFLE CITIZENS



HIGHLIGHT | HIGHLIGHT | HIGHLIGHT

HIDE | HIDE | HIDE

Choose the party to receive the donation of Fr. 30 based on the preferences of the five citizens.

Party	Party	Party
Choose this party ○	Choose this party ○	Choose this party ○
This party reflects the will of the citizens equally well as the chosen party ☐	This party reflects the will of the citizens equally well as the chosen party ☐	This party reflects the will of the citizens equally well as the chosen party ☐

Part C
of this study

This part of the study has 15 rounds. In addition, we will ask some questions about yourself.

Your own payment for this study will be determined by exactly one of the 15 rounds. At the end of this study, the computer will randomly select which round that will be.

Hence, you should make each decision as if it is the one that counts, because it might be!

There are different kinds of decisions in this part. We will explain them as you proceed through the rounds.

←

→

Instructions for the next five rounds

In Part A of this study, you made several decisions concerning how the work tasks will be assigned to five workers recruited from Amazon Mechanical Turk.

In each of the next 5 rounds of part C, we ask you to predict *how much* these workers like or dislike each task assignment.

→

Measuring preference intensity

We have obtained precise measurements of how much each worker likes or dislikes each task. Your task is to predict these measurements.

Specifically, we have measured the least amount of money for which a worker would be willing to complete each task---his *reservation wage* for the task. For instance, if some worker would be willing to complete a task for $1 or more, but would not be willing to complete it for $0.99, then his reservation price is $1. That is the least amount of money for which that worker is willing to complete the task. It is a measure of how bad a worker finds a task – the more he dislikes the task, the more money he must be offered before he will agree to complete it.

As in Part A of this study, we will only tell you a worker's preferences over pre-selected task Assignments. But we will not tell you the specific tasks a worker will complete in those assignments.

Click here if you want to learn more about how we learned about the amounts for which workers are willing to complete each task.

Otherwise scroll to the bottom and click "next".

The screenshot on the right displays the text that is shown only if the subject clicks the button.

Each worker who participated in the first part of this study learned that he faced a five percent chance that his own decisions would determine his payment and the work he would have to complete in the second part of the study.

After ranking the tasks in the order of his preference, each worker completed a list like the following for each of the five tasks.

Complete [task]. In exchange, receive $0.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $1.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $2.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $3.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $4.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $5.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $6.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $7.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $8.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $9.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $10.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $11.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $12.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $13.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $14.	○ ○	Do NOT complete [task], do NOT receive any money.
Complete [task]. In exchange, receive $15.	○ ○	Do NOT complete [task], do NOT receive any money.

Each worker knew that the computer would randomly pick one of the lines of one of the lists. That line would determine the task the worker had to complete, and the payment he would receive for it.

Moreover, the worker knew that in addition to the payment on the line selected to be carried out, he would receive $4 if he followed through with his decision. If he failed to follow through, he would not only forfeit the payment he would have gotten according to the selected line, but he would also lose the $4 he would have received for following through with his decision.

Hence, it was in each worker's own best interest to choose, on each line, as he genuinely preferred.

Predicting preference intensity

In each round of this part, you will make predictions for questions such as the following:

What is the least amount of money for which this worker will agree to complete the Assignment she ranks on the **bottom** (least preferred), out of the three?

$0 $0.50 $1 $1.50 $2 $2.50 $3 $3.50 $4 $4.50 $5 $5.50 $6 $6.50 $7 $7.50 $8 $8.50 $9 $9.50 $10 more than $10

Our payment system is designed such that it is in your own best interest to think about each decision carefully and answer according to your genuine beliefs.

Here's why. If your own study payment is determined by one of the rounds of this part, the following will happen. Many workers have already participated in the first part of this study, and we measured their true reservation wages for each of the assignments. For the round that ends up determining your payment, we will select one of the questions at random. For that question we will compare your answer to the reservation wages we have measured from the workers.

If your prediction coincides with our measurements, the variable part of your payment for this study will be Fr 30. For every dollar by which your prediction differs from the truth, you will lose Fr 3.

For instance, if the true answer is $4, but you select $6, then you are off by two dollars. In this case, the variable part of your payment for the study would be Fr 30 – (2 * Fr 3) = Fr 24.

← →

Memory refresher about mTurk workers

You are predicting the choices of mTurk workers who reside in the United States.

Many of the tasks will take workers **around half an hour** to complete, on average.

A reasonable rule of thumb is that one US-Dollar buys a bit less than one-and-a half times as much in the United States as one Swiss Franc buys in Zurich. At the same time, many workers in the United States also earn substantially less than the average resident of Zurich.

← →

Memory refresher about the tasks

To help you refresh your memory about the five tasks, we will reproduce each of them on the next five pages. Solve one example of each task, then click Next (except for Assigning Apprentices to Mentors, which you do not need to complete).

← →

Subjects proceed through an example of each of the five tasks again.

Memory refresher: Task Assignments

In each round of this part, we are asking you to predict the Workers' reservation wages over three pre-determined task assignments, rather than over each of the five individual tasks. Each of the three Assignments assigns a different task to the worker. You will not learn which tasks are included in the three Assignments for any of the Workers.

← →

Predicting reservation prices
(Round 1 of 5)

In this round, you predictions concern the reservation wages of a worker in a city called **Kalamazoo in the state of Michigan**.

What is the least amount of money for which this worker will agree to complete the Assignment he ranks on **top** (most preferred), out of the three?

$0	$0.50	$1	$1.50	$2	$2.50	$3	$3.50	$4	$4.50	$5	$5.50	$6	$6.50	$7	$7.50	$8	$8.50	$9	$9.50	$10	more than $10
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

What is the least amount of money for which this worker will agree to complete the Assignment he ranks in the **middle** (neither least nor most preferred), out of the three?

$0	$0.50	$1	$1.50	$2	$2.50	$3	$3.50	$4	$4.50	$5	$5.50	$6	$6.50	$7	$7.50	$8	$8.50	$9	$9.50	$10	more than $10
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

What is the least amount of money for which this worker will agree to complete the Assignment he ranks on the **bottom** (least preferred), out of the three?

$0	$0.50	$1	$1.50	$2	$2.50	$3	$3.50	$4	$4.50	$5	$5.50	$6	$6.50	$7	$7.50	$8	$8.50	$9	$9.50	$10	more than $10
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

← →

Your own opinion of the tasks

What is the least amount of money for which **you** would be willing to complete each of the tasks yourself?

(The questions on this page will not affect your payment, and you will not have to complete the tasks. Please answer truthfully.)

Image Labeling. What is the least amount of money for which you would be willing to complete the Image Labeling Task (label **400 images**)?

Fr. 0	Fr. 2	Fr. 4	Fr. 6	Fr. 8	Fr. 10	Fr. 12	Fr. 14	Fr. 16	Fr. 18	Fr. 20	Fr. 22	Fr. 24	Fr. 26	Fr. 28	Fr. 30	More than Fr. 30
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Hate Speech Filtering. What is the least amount of money for which you would be willing to complete the Hate Speech Filtering Task (classify **400 tweets**)?

Fr. 0	Fr. 2	Fr. 4	Fr. 6	Fr. 8	Fr. 10	Fr. 12	Fr. 14	Fr. 16	Fr. 18	Fr. 20	Fr. 22	Fr. 24	Fr. 26	Fr. 28	Fr. 30	More than Fr. 30
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Movie Review Classification. What is the least amount of money for which you would be willing to complete the Movie Review Classification Task (classify **400 reviews**)?

Movie Review Classification Task (classify **400 reviews**)?

Fr. 0	Fr. 2	Fr. 4	Fr. 6	Fr. 8	Fr. 10	Fr. 12	Fr. 14	Fr. 16	Fr. 18	Fr. 20	Fr. 22	Fr. 24	Fr. 26	Fr. 28	Fr. 30	More than Fr. 30
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Assigning Apprentices to Mentors. What is the least amount of money for which you would be willing to complete the Assigning Apprentices to Mentors Task (find assignments for **5 companies**)?

Fr. 0	Fr. 2	Fr. 4	Fr. 6	Fr. 8	Fr. 10	Fr. 12	Fr. 14	Fr. 16	Fr. 18	Fr. 20	Fr. 22	Fr. 24	Fr. 26	Fr. 28	Fr. 30	More than Fr. 30
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Audio Transcription. What is the least amount of money for which you would be willing to complete the Audio Transcription Task (transcribe **400 words**)?

Fr. 0	Fr. 2	Fr. 4	Fr. 6	Fr. 8	Fr. 10	Fr. 12	Fr. 14	Fr. 16	Fr. 18	Fr. 20	Fr. 22	Fr. 24	Fr. 26	Fr. 28	Fr. 30	More than Fr. 30
○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

← →

Instructions for the next six rounds

In Part B of this study, you made several decisions concerning a donation of CHF30 to one of the five biggest Swiss political parties, based on the preferences of Swiss citizens recruited for this study.

In the 5 rounds that follow these instructions, we ask you to predict *how much* these citizens like or dislike the donation going to each of the parties.

Recall the five biggest political parties:

- SP / PS (Social Democratic Party)
- GPS / Verts (Green Party)
- CVP / PDC (Christian Democratic People's Party)
- SVP / UDC (Swiss People's Party)
- FDP / PLR (FDP.The Liberals)

← →

Predicting preference intensity

We have obtained precise measurements of how much each of the citizens in our sample likes or dislikes the donation going to each of the parties.

Your task is to predict these measurements.

Here's how we have made the measurements.

We have elicited each citizen's willingness to pay to trigger or to prevent a donation of Fr. 30 for each of the parties. Each citizen received Fr. 20 for participation in the study. Citizens could use this money to trigger or prevent the donation of Fr. 30.

Specifically, for each party, each citizen made decisions such as this one:

[Party] will receive Fr. 30 and my payment will be reduced by CHF 2
OR
[Party] will receive nothing and my payment will not be reduced.

The amount Fr. 2 is just an example. That amount will vary across your decisions.

Somebody who wishes the party had more money and is willing to pay Fr. 2 to increase the party's budget by Fr. 30 will select the first option. Somebody who does not like the party or who does not want to give up Fr. 2 to increase the party's budget by Fr. 30 will select the second option.

Each citizen also made decisions like this one:

[Party] will receive nothing and my payment will be reduced by CHF 2
OR
[Party] will receive Fr. 30 and my payment will not be reduced.

The amount Fr. 2 is just an example. That amount will vary across your decisions.

Somebody who wishes the party had less money and is willing to pay Fr. 2 to prevent the donation of Fr. 30 to the party will select the first option. Somebody who likes the party or who does not want to give up Fr. 2 to prevent the donation Fr. 30 to the party will select the second option.

Hence, we know, for each citizen, how much money they are willing to pay to trigger or prevent the donation of Fr. 30

Your task

Your task is to predict, for five randomly chosen voters, how much they are willing to pay to trigger or prevent the donation of Fr. 30 to each of three of the five parties, selected at random. You will only know whether your prediction concerns the citizen's most-preferred, middle, or least-preferred party amongst the random selection of three parties, but you will not know which party the citizen has ranked in which place. Neither will you know which parties are in the randomly selected set of three parties. You will make your prediction like this:

How much is this citizen willing to pay to trigger or prevent a donation of Fr. 30 to the party she ranks in **the middle** (neither most nor least preferred), out of the three?

- ○ more than CHF 15 to trigger the donation
- ○ up to CHF 15 to trigger the donation
- ○ up to CHF 10 to trigger the donation
- ○ up to CHF 7.50 to trigger the donation
- ○ up to CHF 5 to trigger the donation
- ○ up to CHF 4 to trigger the donation
- ○ up to CHF 3 to trigger the donation
- ○ up to CHF 2 to trigger the donation
- ○ up to CHF 1 to trigger the donation
- ○ up to CHF 1 to prevent the donation
- ○ up to CHF 2 to prevent the donation
- ○ up to CHF 3 to prevent the donation
- ○ up to CHF 4 to prevent the donation
- ○ up to CHF 5 to prevent the donation
- ○ up to CHF 7.50 to prevent the donation
- ○ up to CHF 10 to prevent the donation
- ○ up to CHF 15 to prevent the donation
- ○ more than CHF 15 to prevent the donation

Our payment system is designed such that it is in your own best interest to think about each decision carefully and answer according to your genuine beliefs.

Here's why. If your own study payment is determined by one of the rounds of this part, the following will happen. Many citizens have already participated in the first part of this study, and we measured their willingness to pay to trigger or prevent the donation to each of the five parties. For the round that ends up determining your payment, we will select one of the questions at random. For that question, we will compare your answer to the measurement we have obtained from the citizen whose willingness to pay you are predicting.

If your prediction coincides with our measurements, the variable part of your payment for this study will be Fr 30. For every Franc by which your prediction differs from the truth, you will lose Fr 1.

For instance, if the true answer is that the citizen is willing to pay Fr. 4 to *trigger* the donation, but you think the citizen is willing to pay Fr. 10 to *prevent* the donation, then you are off by Fr. 14. In this case, the variable part of your payment for the study would be Fr 30 – (14 * Fr 1) = Fr 16.

Predicting Swiss citizens' preferences
(Round 1 of 5)

In this round, you predictions concern the preferences of a Swiss citizen whose first name is

Seraina.

SVP UDC CVP GRÜNE LES VERTS SP FDP Die Liberalen

We have randomly selected three of the five parties above.

How much is this citizen willing to pay to trigger or prevent a donation of Fr. 30 to the party she ranks **on top** (most preferred), out of the three?

- ○ more than CHF 15 to trigger the donation
- ○ up to CHF 15 to trigger the donation
- ○ up to CHF 13 to trigger the donation
- ○ up to CHF 11 to trigger the donation
- ○ up to CHF 9 to trigger the donation
- ○ up to CHF 7 to trigger the donation
- ○ up to CHF 5 to trigger the donation
- ○ up to CHF 3 to trigger the donation
- ○ up to CHF 1 to trigger the donation
- ○ up to CHF 1 to prevent the donation
- ○ up to CHF 3 to prevent the donation
- ○ up to CHF 5 to prevent the donation
- ○ up to CHF 7 to prevent the donation
- ○ up to CHF 9 to prevent the donation
- ○ up to CHF 11 to prevent the donation
- ○ up to CHF 13 to prevent the donation
- ○ up to CHF 15 to prevent the donation
- ○ more than CHF 15 to prevent the donation

On the same page, the subject also answers the following two questions:

- *How much is this citizen willing to pay to trigger or prevent a donation of Fr. 30 to the party she ranks in the middle (neither most nor least preferred), out of the three?*
- *How much is this citizen willing to pay to trigger or prevent a donation of Fr. 30 to the party she ranks on the bottom (least preferred), out of the three?*

The subject answers the same three questions for another (real) four Swiss citizens, all with common Swiss first names. A random half of subjects see the above three questions in reverse order, i.e. starting with the citizen's bottom preference.

Round 12 of 15 in part C

Your own opinion of the parties

What is the largest amount of money that **you** would be willing to pay to trigger or prevent a donation to each of the five political parties?

*(The questions on this page are hypothetical. They will **not** affect your payment, and will not trigger or prevent a donation. Please answer truthfully.)*

Are you eligible to vote in Switzerland?

○ Yes

How much are you willing to pay to trigger or prevent a donation of Fr. 30 to the FDP / PLR (FDP.The Liberals)

FDP
Die Liberalen

I would be willing to pay ...

○ more than CHF 15 to trigger the donation
○ up to CHF 15 to trigger the donation
○ up to CHF 10 to trigger the donation
○ up to CHF 7.50 to trigger the donation
○ up to CHF 5 to trigger the donation
○ up to CHF 4 to trigger the donation
○ up to CHF 3 to trigger the donation
○ up to CHF 2 to trigger the donation
○ up to CHF 1 to trigger the donation
○ up to CHF 1 to prevent the donation
○ up to CHF 2 to prevent the donation
○ up to CHF 3 to prevent the donation
○ up to CHF 4 to prevent the donation
○ up to CHF 5 to prevent the donation
○ up to CHF 7.50 to prevent the donation
○ up to CHF 10 to prevent the donation
○ up to CHF 15 to prevent the donation
○ more than CHF 15 to prevent the donation

On the same page, the subject answers the same question for each of the remaining four parties (parties presented in random order).

In each of the next 2 rounds, you will see a list of lotteries like this one:

On each line, chose the option you genuinely prefer.

Receive 18 Fr. with 0% chance or 12 Fr. with 100% chance.	○	○	Receive 30 Fr. with 0% chance or 3 Fr. with 100% chance.
Receive 18 Fr. with 10% chance or 12 Fr. with 90% chance.	○	○	Receive 30 Fr. with 10% chance or 3 Fr. with 90% chance.
Receive 18 Fr. with 20% chance or 12 Fr. with 80% chance.	○	○	Receive 30 Fr. with 20% chance or 3 Fr. with 80% chance.
Receive 18 Fr. with 30% chance or 12 Fr. with 70% chance.	○	○	Receive 30 Fr. with 30% chance or 3 Fr. with 70% chance.
Receive 18 Fr. with 40% chance or 12 Fr. with 60% chance.	○	○	Receive 30 Fr. with 40% chance or 3 Fr. with 60% chance.
Receive 18 Fr. with 50% chance or 12 Fr. with 50% chance.	○	○	Receive 30 Fr. with 50% chance or 3 Fr. with 50% chance.
Receive 18 Fr. with 60% chance or 12 Fr. with 40% chance.	○	○	Receive 30 Fr. with 60% chance or 3 Fr. with 40% chance.
Receive 18 Fr. with 70% chance or 12 Fr. with 30% chance.	○	○	Receive 30 Fr. with 70% chance or 3 Fr. with 30% chance.
Receive 18 Fr. with 80% chance or 12 Fr. with 20% chance.	○	○	Receive 30 Fr. with 80% chance or 3 Fr. with 20% chance.
Receive 18 Fr. with 90% chance or 12 Fr. with 10% chance.	○	○	Receive 30 Fr. with 90% chance or 3 Fr. with 10% chance.
Receive 18 Fr. with 100% chance or 12 Fr. with 0% chance.	○	○	Receive 30 Fr. with 100% chance or 3 Fr. with 0% chance.

If one of these rounds determines the payment you will receive for this study, here's what will happen. The computer will randomly draw one of lines from the list in that round. The computer will then play out the lottery you selected on that line. That lottery will determine the variable part of the payment you receive for this study.

Hence, you should make each decision on each line as if it is the one that counts, because it might be!

→

Choice between lotteries.

On each line, chose the option you genuinely prefer.

Receive 20 Fr with 0% chance or 13 Fr with 100% chance.	○ ○	Receive 34 Fr with 0% chance or 5 Fr with 100% chance.
Receive 20 Fr with 10% chance or 13 Fr with 90% chance.	○ ○	Receive 34 Fr with 10% chance or 5 Fr with 90% chance.
Receive 20 Fr with 20% chance or 13 Fr with 80% chance.	○ ○	Receive 34 Fr with 20% chance or 5 Fr with 80% chance.
Receive 20 Fr with 30% chance or 13 Fr with 70% chance.	○ ○	Receive 34 Fr with 30% chance or 5 Fr with 70% chance.
Receive 20 Fr with 40% chance or 13 Fr with 60% chance.	○ ○	Receive 34 Fr with 40% chance or 5 Fr with 60% chance.
Receive 20 Fr with 50% chance or 13 Fr with 50% chance.	○ ○	Receive 34 Fr with 50% chance or 5 Fr with 50% chance.
Receive 20 Fr with 60% chance or 13 Fr with 40% chance.	○ ○	Receive 34 Fr with 60% chance or 5 Fr with 40% chance.
Receive 20 Fr with 70% chance or 13 Fr with 30% chance.	○ ○	Receive 34 Fr with 70% chance or 5 Fr with 30% chance.
Receive 20 Fr with 80% chance or 13 Fr with 20% chance.	○ ○	Receive 34 Fr with 80% chance or 5 Fr with 20% chance.
Receive 20 Fr with 90% chance or 13 Fr with 10% chance.	○ ○	Receive 34 Fr with 90% chance or 5 Fr with 10% chance.
Receive 20 Fr with 100% chance or 13 Fr with 0% chance.	○ ○	Receive 34 Fr with 100% chance or 5 Fr with 0% chance.

← →

Choice between lotteries.

On each line, chose the option you genuinely prefer.

Receive 23 Fr with 0% chance or 15 Fr with 100% chance.	○ ○	Receive 38 Fr with 0% chance or 3 Fr with 100% chance.
Receive 23 Fr with 10% chance or 15 Fr with 90% chance.	○ ○	Receive 38 Fr with 10% chance or 3 Fr with 90% chance.
Receive 23 Fr with 20% chance or 15 Fr with 80% chance.	○ ○	Receive 38 Fr with 20% chance or 3 Fr with 80% chance.
Receive 23 Fr with 30% chance or 15 Fr with 70% chance.	○ ○	Receive 38 Fr with 30% chance or 3 Fr with 70% chance.
Receive 23 Fr with 40% chance or 15 Fr with 60% chance.	○ ○	Receive 38 Fr with 40% chance or 3 Fr with 60% chance.
Receive 23 Fr with 50% chance or 15 Fr with 50% chance.	○ ○	Receive 38 Fr with 50% chance or 3 Fr with 50% chance.
Receive 23 Fr with 60% chance or 15 Fr with 40% chance.	○ ○	Receive 38 Fr with 60% chance or 3 Fr with 40% chance.
Receive 23 Fr with 70% chance or 15 Fr with 30% chance.	○ ○	Receive 38 Fr with 70% chance or 3 Fr with 30% chance.
Receive 23 Fr with 80% chance or 15 Fr with 20% chance.	○ ○	Receive 38 Fr with 80% chance or 3 Fr with 20% chance.
Receive 23 Fr with 90% chance or 15 Fr with 10% chance.	○ ○	Receive 38 Fr with 90% chance or 3 Fr with 10% chance.
Receive 23 Fr with 100% chance or 15 Fr with 0% chance.	○ ○	Receive 38 Fr with 100% chance or 3 Fr with 0% chance.

← →

Instructions for the next two rounds

In each of the next two rounds, you decide whether the five workers will receive additional payments (independently of the task assignment you have decided about in Part A).

Your task is to select the options you genuinely prefer on each line of a list such as the one below.

On each line, you decide whether to increase each of the five workers' payments by some amount at a cost to yourself.

Increase each of the five workers' payoffs by $2. Leave my own study payment unchanged.	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 1**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 2**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 3**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 4**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 6**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 8**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 10**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 12**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 14**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 16**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 18**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **CHF 20**	○ ○	Do not increase the group members' payoffs. Leave my own study payment unchanged.

If one of these two parts is randomly selected to determine your study payment, the variable part of your payment will be Fr. 30 minus whatever you choose to give up to effect an increase in the Workers' payments. (In addition, you will receive the fixed payment of Fr. 30.)

Specifically, at the end of the study, the computer will randomly select exactly one of these lines. Whatever you have selected on that line will be carried out. If, on the chosen line, you select the option on the right, you will receive CHF 30, and the five MTurk workers assigned to you will not receive any additional payment other than what they expect to receive for completing the tasks assigned to them. If, on the chosen line, you select the option on the left, we will pay each of the five MTurk workers assigned to you the specified additional amount of money, and we will discount the amount mentioned on the selected line from the Fr. 30 you would otherwise have received.

Hence, you should make each decision on each line as if it is the one that counts, because it might be!

← →

On each line, select the option you genuinely prefer

(At the current exchange rate, USD 1 = Fr. 0.90.)

Increase each of the five workers' payoffs by $2. Leave my own study payment unchanged.	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 1**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 2**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 3**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 4**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 6**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 8**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 10**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 12**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 14**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 16**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 18**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by $2. Decrease my own study payment by **Fr. 20**	○ ○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.

← →

On each line, select the option you genuinely prefer

(At the current exchange rate, USD 1 = Fr. 0.90.)

Increase each of the five workers' payoffs by **Fr. 0.20** (exchanged to USD). Decrease my own study payment by **Fr. 1**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 0.40** (exchanged to USD). Decrease my own study payment by **Fr. 2**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 0.60** (exchanged to USD). Decrease my own study payment by **Fr. 3**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 0.80** (exchanged to USD). Decrease my own study payment by **Fr. 4**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 1** (exchanged to USD). Decrease my own study payment by **Fr. 5**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 1.20** (exchanged to USD). Decrease my own study payment by **Fr. 6**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 1.40** (exchanged to USD). Decrease my own study payment by **Fr. 7**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 1.60** (exchanged to USD). Decrease my own study payment by **Fr. 8**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 1.80** (exchanged to USD). Decrease my own study payment by **Fr. 9**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.
Increase each of the five workers' payoffs by **Fr. 2** (exchanged to USD). Decrease my own study payment by **Fr. 10**	○	○	Do not increase the five workers' payoffs. Leave my own study payment unchanged.

← →

Finally, we would like to ask you some questions about yourself.

Please answer truthfully.

What is your gender?

- ○ Male
- ○ Female
- ○ Other (e.g. genderqueer)

What is your age?

At which institution / faculty is your main field of study?

- ○ UZH Theological faculty
- ○ UZH Law
- ○ UZH Business, economics, and informatics
- ○ UZH Medicine
- ○ UZH Vetsuisse
- ○ UZH Philosophical faculty
- ○ UZH Mathematics and sciences
- ○ ETH Architecture and civil engineering
- ○ ETH Engineering sciences
- ○ ETH Natural sciences and mathematics
- ○ ETH Systems-oriented natural sciences
- ○ ETH Management and social sciences
- ○ ZHAW Linguistics, psychology, or social work
- ○ ZHAW Architecture, Design and Civil Engineering
- ○ ZHAW Engineering
- ○ ZHAW Health Professions
- ○ ZHAW Life Sciences and Facility Management
- ○ ZHAW Management and Law
- ○ ZHDK
- ○ Other

What degree level are you currently working towards

- ◯ Bachelor
- ◯ Master
- ◯ Doctorate
- ◯ Postdoc
- ◯ I am not currently working towards a degree

What was your final grade in your Maturität in Mathematics?

- ◯ 6
- ◯ 5.5
- ◯ 5
- ◯ 4.5
- ◯ 4
- ◯ 3.5
- ◯ 3
- ◯ 2.5
- ◯ 2
- ◯ 1.5
- ◯ 1
- ◯ I do not have a Swiss high school degree (Maturität)

What was your final grade in your Maturität in your main language (German / French / Italian)?

- ◯ 6
- ◯ 5.5
- ◯ 5
- ◯ 4.5
- ◯ 4
- ◯ 3.5
- ◯ 3
- ◯ 2.5
- ◯ 2
- ◯ 1.5
- ◯ 1
- ◯ I do not have a Swiss high school degree (Maturität)

What is your native language?

- ◯ German
- ◯ French
- ◯ Italian
- ◯ Rumansch
- ◯ English
- ◯ Other. Please indicate. ________

In which canton did you obtain your Maturität?

- ◯ AG
- ◯ AI
- ◯ AR
- ◯ BE
- ◯ BL
- ◯ BS
- ◯ FR
- ◯ GE
- ◯ GL
- ◯ GR
- ◯ JU
- ◯ LU
- ◯ NE
- ◯ NW
- ◯ OW
- ◯ SG
- ◯ SH
- ◯ SO
- ◯ SZ
- ◯ TG
- ◯ TI
- ◯ UR
- ◯ VD
- ◯ VS
- ◯ ZG
- ◯ ZH
- ◯ I do not have a Swiss high school degree (Maturität)

Do you currently live with your parents?

- Yes
- No

How many siblings do you have?

- None
- 1
- 2
- 3
- 4
- more than 4

How much money do you spend per month, on average? (Including food, rent, clothing, entertainment. If your spending has changed during the Covid19-crisis, please indicate your spending from *before* the crisis.)

- CHF500 or less
- Between CHF500 and CHF1000
- Between CHF1000 and CHF1500
- Between CHF1500 and CHF2000
- Between CHF2000 and CHF2500
- Between CHF2500 and CHF3000
- Between CHF3000 and CHF4000
- Between CHF4000 and CHF5000
- Between CHF 5000 and CHF7500
- Between CHF7500 and CHF10000
- CHF10000 or more

← →

How religious are you?

- I am deeply religious
- I am somewhat religious
- I am not very religious
- I am not religious at all

If you have one, what is your religion?

- Christian (protestant)
- Christian (catholic)
- Muslim
- Judaist
- Hindu, Buddist, or Sikh
- Agnostic or atheist

Where do you stand politically?

- Far right
- Right
- Right of center
- Center
- Left of center
- Left
- Far left

If you are Swiss, which political party have you voted for in the last election of the Nationalrat / Conseil national / Consiglio nazionale / Cussegl naziunal? (If you have not voted but you are eligible to vote, please indicate the party you would vote for in the next election.)

- Lega dei Ticinesi
- EDU / UDF
- Grüne / Verts
- solidaritéS
- SP / PS
- GLP / vertlibéraux
- BDP / PBD
- FDP / PLR
- SVP / UDC
- PdA / PST
- CVP / PDC
- Other
- I am not eligible to vote in Switzerland
- EVP / PEV

← →

If you're running a race and you pass the person in second place, what place are you in?

- First
- Second
- Third

A farmer had 15 sheep and all but 8 died. How many are left?

Emily's father has three daughters. The first two are named April and May. What is the third daughter's name?

How many cubic feet of dirt are there in a hole that is 3' deep, 3' wide, and 3' long?

← →

The following table illustrates one of the most famous paradoxes of voting theory. If you know the name of the paradox, please enter it below:

Voter	First preference	Second preference	Third preference
Voter 1	A	B	C
Voter 2	B	C	A
Voter 3	C	A	B

The following is a description of a well-known voting rule. If you know its name, please enter it below:

The winner of an election is determined by giving each candidate, for each ballot, a number of points corresponding to the number of candidates ranked lower. Once all votes have been counted, the option or candidate with the most points is the winner.

The following is an informal statement of one of the foundational theorems in the theory of social choice. If you know it's name, please enter it below:

If there are at least 3 alternatives, there is no social choice function that simultaneously satisfies (i) unrestricted domain, (ii) unanimity, (iii) independence of irrelevant alternatives, and (iv) non-dictatorship.

Have you ever taken a class that covered the theory of social choice?

- Yes
- No

← →

This is the end of this study.

Your payment for participating in this study consists of the fixed payment of **CHF 30** plus the variable payment of **CHF 34** for a total of

CHF 64.

The variable part of your payment has been determined by one of your choices between lotteries. From the choices you have made, one line was selected at random, and the corresponding lottery was played out, exactly as described in the instructions.

Please click the NEXT button to be redirected to the payment form.

E.2 General population experiment

Technical Check

To test whether your computer can display the study correctly, please copy the following number into the field below

19

→

WELCOME

This is a research study run by the Departments of Economics at Stanford University and at the University of Zurich.

This study will take **20-30 minutes** to complete.

By clicking the "continue" button below, you consent to participating in this decision making study.

DESCRIPTION: You are invited to participate in a research study about how people make choices for others. We will show you some information about other peoples' preferences, and then we will ask you to make decisions for them. (Principal Investigators: Sandro Ambuehl, University of Zurich and B. Douglas Bernheim, Stanford University)

SENSITIVE QUESTIONS: We will ask you about your political attitudes.

TIME INVOLVEMENT: The survey will take 20-30 minutes

RISKS AND BENEFITS: There are no risks associated with this study. We cannot and do not guarantee or promise that you will receive any benefits from this study.

DATA USAGE: Your data is anonymous. The data will be analyzed for scientific purposes and will be made available to other researchers through platforms such as the Harvard Dataverse.

COMPENSATION: You will receive the standard panel compensation for completing this survey.

PARTICIPANT'S RIGHTS: If you have read this form and have decided to participate in this project, please understand your participation is voluntary and you have the right to withdraw your consent or discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled. The alternative is not to participate. You have the right to refuse to answer particular questions. The results of this research study may be presented at scientific or professional meetings or published in scientific journals. Your individual privacy will be maintained in all published and written data resulting from the study.

CONTACT INFORMATION:

Independent Contact: If you are not satisfied with how this study is being conducted, or if you have any concerns, complaints, or general questions about the research or your rights as a participant, please contact the Stanford Institutional Review Board (IRB) to speak to someone independent of the research team at (650)-723-2480 or toll free at 1-866-680-2906, or email at IRB2-Manager@lists.stanford.edu. You can also write to the Stanford IRB, Stanford University, 1705 El Camino Real, Palo Alto, CA 94306.

I AGREE to participate ○

I do NOT agree to participate ○

What is your age

- 18-25
- 26-35
- 36-45
- 46-55
- 56-65
- 66-75
- 76-85
- 85 or older

What is your gender

- Female
- Male
- Other (e.g. non-binary)

What is your primary ethnicity?

- Black or African American
- Native Hawaiian or Pacific Islander
- White (non-hispanic)
- American Indian or Alaska Native
- White (hispanic)
- Asian
- Other

In which state do you currently reside?

Are you a US citizen?

- Yes
- No

Where do you stand politically?

Clearly left	Slightly left	Center	Slightly right	Clearly right
○	○	○	○	○

Which of the following political parties is closest to your own views and values?

- Democratic Party
- Republican Party
- Constitution Party
- Libertarian Party
- American Solidarity Party
- Green Party

What is the highest level of education you have completed?

- Some high school
- High school diploma or GED
- Some college, but no degree
- Associates degree
- Bachelor's degree
- Master's degree
- PhD or professional doctorate (such as MD, JD, etc.)

What is your marital status?

- Married
- Widowed
- Divorced
- Separated
- Never married

What is your annual income?

- Less than $10,000
- $10,000 - $19,999
- $20,000 - $29,999
- $30,000 - $39,999
- $40,000 - $49,999
- $50,000 - $59,999
- $60,000 - $69,999
- $70,000 - $79,999
- $80,000 - $89,999
- $90,000 - $99,999
- $100,000 - $149,999
- More than $150,000

What is your employment status?

- Employed full time
- Employed part time
- Unemployed looking for work
- Unemployed not looking for work
- Retired
- Student
- Disabled

Instructions

Please read the instructions carefully.

In this study, you will make decisions about a $20 donation to one of the following charitable organizations:

- unicef **UN International Children's Emergency Fund** is an agency that provides aid to children worldwide. It works to save children's lives, to defend their rights, and to help them fulfil their potential, from early childhood through adolescence.
- IFAW **The International Fund for Animal Welfare** is one of the largest animal welfare and conservation charities in the world. The organization works to rescue individual animals, safeguard populations, preserve habitat, and advocate for greater protections.
- OXFAM **Oxfam** is an international organization (NGO) that works to alleviate global poverty. It aims to help people build better lives for themselves, and for others
- **Doctors Without Borders** is an international organization (NGO) that provides lifesaving medical humanitarian care in conflict zones and in countries affected by endemic diseases.

→

Your decisions

We have enlisted five US citizens to participate in a first part of this study. Each of the five citizens ranked the charitable organizations according to how much or how little he or she would like that charity to receive the donation of $20.

Your task in this study is to select one of the charitable organizations based on the preferences of the five citizens assigned to you. The donation will go to exactly one of the charitable organizations. You cannot split up the donation.

The five US citizens assigned to you are not assigned to any other study participant. Hence, you are the only person who decides based on the preferences of these five citizens.

There is a one in ten chance that your choices will determine which charitable organization will receive the money.

Hence, please make every decision as if will be carried out -- it might be!

On behalf of the Economics Departments at Stanford University and at the University of Zurich, we guarantee that we carry out all aspects of the study exactly as we describe to you. The rules governing our research do not permit us to deceive our participants in any way.

← →

The 12 rounds

You make decisions in 12 rounds. In one of these rounds, you will see the preferences of the five US citizens assigned to you. Your choice of a charity for that round is real, and we will carry it out with a 1 in 10 chance. However, we are not going to tell you which round involves your real choice. Please treat every one of these rounds as if it were real -- it could be!

We ask you to decide based on the will of the group as a whole, taking into account their preferences and disagreements, but ignoring your own preferences concerning the charitable organizations.

That's why we anonymize the charities. We will not refer to the them by their names but by abstract symbols like , , or . Each symbol represents the donation going to a specific organization. For instance, symbol might indicate that the donation goes to Doctors Without Borders, symbol might indicate that the donation goes to UNICEF, etc. (Don't bother to remember these symbols, they are just examples. They have absolutely no meaning, apart from serving as labels to help you visually distinguish between the charities).

← →

The US citizens' preferences

To help you decide which organization will receive the donation of $20, you will see the preferences of each of the five US citizens over the organizations in a picture such as this one:

Each bar represents one of the charitable organizations you can choose.

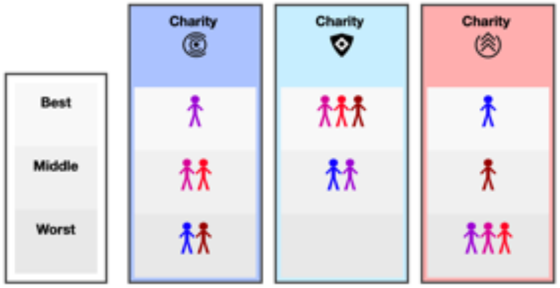
Each bar contains five stick figures ( ) which represent the five US citizens to whom you are assigned. Within each bar, each citizen is placed into one of three cells labeled "Best", "Middle" and "Worst", depending on how much he likes or dislikes the corresponding charitable organization to receive the donation of $20. Consider the bar on the very left (the charity represented by symbol), for instance. Within this bar, two citizens (and) are in the cell labeled "Best". Another three citizens (, , and) are in the cell labeled "Worst". Hence, charity is the one that citizen most prefers to receive the donation of $20, from amongst the three charities in this picture. Similarly, the charity represented by symbol is the one that citizen most prefers to receive the donation.

However, charity is the one that citizen least prefers to receive the donation amount, from amongst the three charities in this picture. It is also the one that tcitizens and prefer least.

Now look at the bar on the very right (the charity represented by symbol). In that bar, all citizen symbols are in the cell labeled "middle". Charity is the one that citizen , for instance, ranks in the middle, out of the three charities in this picture. It is also the charity each remaining citizen ranks in the middle.

Comprehension Check 1

To make sure you correctly understand the information about the five US citizens' preferences, please answer the questions below. (This page shows *different* preferences than those displayed on the previous page.)



How many citizens rank charity on top (most preferred)?

0	1	2	3	4	5
○	○	○	○	○	○

Which Charity does prefer least?

Charity	Charity	Charity
○	○	○

Where does rank Charity ?

Top	Middle	Bottom
○	○	○

← →

Your task is to make the choice you believe is best for the group as a whole in light of its members' preferences.

To help you study the citizens' preferences, there are several options for rearranging, highlighting, and hiding information in the picture if you find it helpful. You don't have to use these interactive features, but we want you to know they're available.

We'll now walk you through each of the features. Please click "next" (the button with the arrow to the lower right) to start.

← →

Subjects see each of the following statements, and complete the requested action before the next statement is shown.

(i) You can drag and drop each charity to a different position. Please give this a try by dragging one charity to a different location.

(ii) On each bar, just above the stick figures representing the citizens, you see a button labeled 'hide.' If you click it, the citizen's preferences about that charity will be hidden. If you click it again, they will be shown again. Please hide, then show, citizen's preferences about one of the charities.

(iii) If you hide one of the charities, only two charities remain. The picture then places the citizens into the cells according to which of the **two** charities they find better. The picture is still showing the same preference information by the same citizens! To see this, please again hide, then show, one of the charities.

(iv) At the bottom of the figure, you see two rows of buttons. Buttons in the top row let you hide and show individual citizens. Please hide, then show, one of the citizens.

(v) At the bottom of the figure, you see two rows of buttons. Buttons in the top row let you hide and show individual citizens. Please hide, then show, one of the citizens.

(vi) Buttons in the bottom row let you highlight individual citizens. Please highlight, then un-highlight one of the citizens.

(vii) Finally, at the top of the picture you see a button labeled 'Shuffle charities.' That button will shuffle the order in which the charities are displayed. Please click it.

(viii) Great, that's all the features. Please click "next" to continue.

In some rounds, only three of the four charities will be available. If so, your decision concerns the following three charities:

(They were randomly selected by the computer at the beginning of this survey.)

- unicef **UN International Children's Emergency Fund** is an agency that provides aid to children worldwide. It works to save children's lives, to defend their rights, and to help them fulfil their potential, from early childhood through adolescence.
- OXFAM **Oxfam** is an international organization (NGO) that works to alleviate global poverty. It aims to help people build better lives for themselves, and for others
- **Doctors Without Borders** is an international organization (NGO) that provides lifesaving medical humanitarian care in conflict zones and in countries affected by endemic diseases.

← →

Comprehension Check

Before you start with your decisions, please check all the correct statements below (and only those).

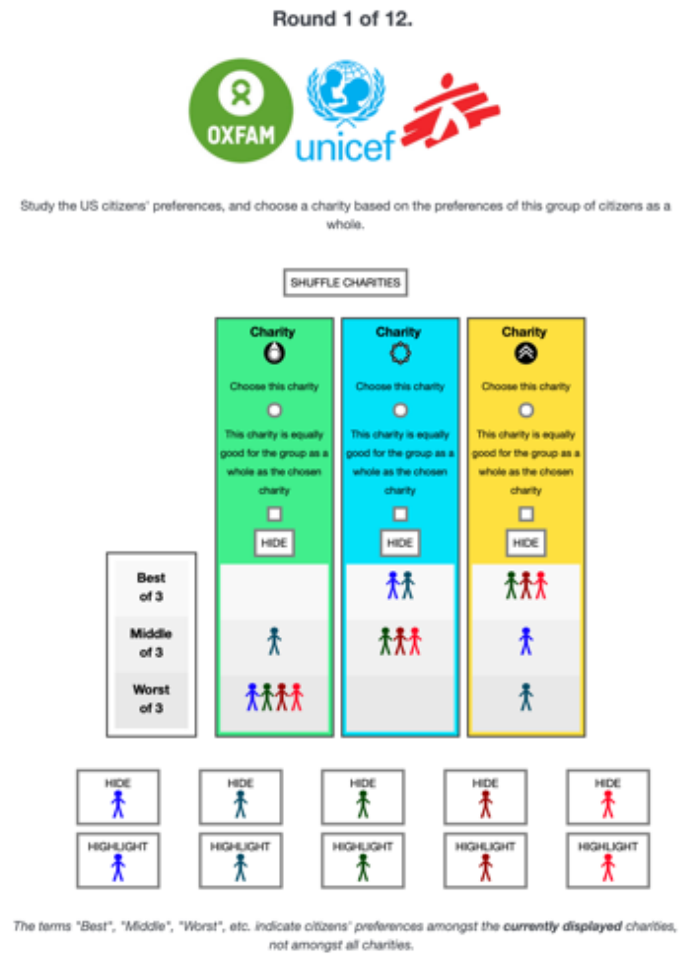
- ☐ The five US citizens have already participated in a first part of the experiment in which they ranked the four charities according to how much / how little they would like them to receive the donation of $20.
- ☐ The five US citizens are real. My choice of a charitable organization based on their preferences will determine which charitable organization will receive a donation (if this part of the study is randomly chosen to be carried out).
- ☐ Exactly one round is the "real" one: In that round I see the true preferences of the five US citizens. With a 1 in 10 chance, my decision in that round will determine which charitable organization will receive the donation of $20.
- ☐ The five US citizens are hypothetical, and no donation will actually be made to a charitable organization.

← →

Your decisions begin now.

Please make each decision as if it is the one that counts, because it might be!

→



Questions

Finally, we would like to ask you a few questions about yourself and about the charities. Please answer truthfully.

How familiar are you with the charitable organizations?

	I have never heard of this charity before	I have heard about this charity in the past	I know this charity well
OXFAM Oxfam	○	○	○
Doctors without Borders	○	○	○
IFAW International Fund for Animal Welfare	○	○	○
unicef UN International Children's Emergency Fund	○	○	○

→

What do you think the average American thinks of each of the four charities?

The average American thinks that the work of the charity on the left is ...

	... much less important than that of the other three charities	... a bit less important than that of the other three charities	... just as important as that of the other three charities	... a bit more important than that of the other three charities	... a lot more important than that of the other three charities
IFAW International Fund for Animal Welfare	○	○	○	○	○
Doctors without Borders	○	○	○	○	○
OXFAM Oxfam	○	○	○	○	○
unicef UN International Children's Emergency Fund	○	○	○	○	○

← →

Consider two possible candidates for political leadership of the nation.

- Candidate 1 is compromising. While he is nobody's greatest favorite, most citizens would be ok with candidate 1. If he were elected, nobody would be exhilarated, nobody would be devastated.
- Candidate 2 is polarizing. Most citizens either love him or hate him. There is hardly anyone who does not have a strong opinion. If candidate 2 were elected, some citizens would be exhilarated, many others would be devastated, and nobody would be indifferent.

Which candidate better represents the will of the citizens of the nation?

Candidate 1	Candidate 2
○	○

← →

Please indicate your level of agreement with both of the following statements

The political system should strive for compromise solutions that everyone can live with even if the result is nobody's absolute favorite.

Strongly disagree	Disagree	Agree	Strongly agree
○	○	○	○

What the majority wants is right for a country, even if that makes some citizens suffer.

Strongly disagree	Disagree	Agree	Strongly agree
○	○	○	○

← →

How do you see yourself: are you a person who is generally willing to take risks, or do you try to avoid taking risks?

- Very willing to take risk
- Somewhat willing to take risks
- Somewhat unwilling to take risks
- Very unwilling to take risks

How well does the following statement describe you as a person? As long as I am not convinced otherwise, I assume that people have only the best intentions.

- Does not describe me at all
- Does not describe me very well
- Describes me somewhat well
- Describes me very well

How do you assess your willingness to share with others without expecting anything in return when it comes to charity?

- Completely unwilling to share
- Somewhat unwilling to share
- Somewhat willing to share
- Very willing to share

Do you work in a job in which you routinely make decisions that affect groups of people (e.g. manager)?

- Yes
- No

← →

This is the end of this study.

We very much appreciate your participation!

← →

E.3 Elicitation of mTurk worker Stakeholder preferences

Technical Check

To test whether your computer can display the study correctly, please copy the following number into the field below

189214

← →

To see if you are eligible to participate, please enter your Mechanical Turk Worker ID into the box below and then click NEXT.

Please see below for where you can find your Worker ID. Your WorkerID starts with the letter A and has 12-14 letters or numbers. It must be all CAPITAL letters and no spaces. It is NOT your email address.

→

WELCOME

This is a research study run by Stanford University and the University of Zurich.

IMPORTANT

This is a two-part study. Please only take this study if you will be able to complete *both* parts. There will be a one to two weeks delay between the first and second part.

The first part will take about 4 minutes to complete. You will earn the HIT payment of $0.50 for completing that part.

Between one and four weeks after finishing the first part, you will receive an invitation to participate in the second part. That part will take up to 45 minutes to complete, but, depending on your decisions and speed, could be much shorter. You will receive an invitation for the second part through a penny-bonus with a link. On average, you will then receive a bonus of $10 for completing the second part.

Informed Consent

PROTOCAL DIRECTORS:

B. Douglas Bernheim and Jonas Anselm Mueller-Gastell, Stanford University, Department of Economics.

DESCRIPTION: You are invited to participate in a research study on decision-making. You will be asked to read instructions on screen and/or on paper in the beginning and throughout the experiment. You will be asked to make several choices (by using a computer terminal) and answer several survey questions. You will also be asked to make other decisions that do not affect your payment.

PAYMENTS: You will receive the HIT payment upon completion of this study.

TIME INVOLVEMENT: Your participation in the first part of this experiment will take around 10 minutes.

YOUR RIGHTS: If you have read this form and have decided to participate in this project, please understand your participation is voluntary and you have the right discontinue participation at any time. If you choose to do so, your payment will be $0. Your individual privacy will be maintained in all published and written data resulting from the study. We will record your Internet Protocal address (IP address) to exclude duplicate survey respondents.

CONFLICT OF INTEREST STATEMENT: None of the researchers involved with this study have any conflict of interest.

CONTACT INFORMATION: If you have any questions, concerns or complaints or if you feel that you have been injured as a result of participating in the study, please contact Matias Cersosimo, Stanford University, Department of Economics, mati_cersosimo@stanford.edu, (650) 387 9919.

INDEPENDENT CONTACT: If you are not satisfied with how this study is being conducted, or if you have any concerns, complaints, or general questions about the research or your rights as a participant, please contact the Stanford University Research Compliance Office, 3000 El Camino Real, Five Palo Alto Square, 4th Floor, Palo Alto, CA 94306, (650)723-2480 to speak to someone independent of the research team.

By clicking the "continue" button below, you consent to participating in this decision making study.

Instructions

Please read carefully.

If you have questions about the instructions, please send an email to sandro.ambuehl@econ.uzh.ch for assistance.

Five different work tasks

In this part of this study, you will make several decisions regarding the task you will complete in part 2 (in one to four weeks from today).

Once we send you the link for part 2, you will have one week to complete that part.

There are five different work tasks, of which you will complete one in part 2. If you do complete the assigned task at that time, you will receive a bonus payment of, on average, $10.

To help you with your decision, on the next five pages, you will see a brief example of each of the five work tasks. For each of the five tasks, the "next" button will appear as soon as you have provided one correct answer.

→

Movie Review Classification (task 1)

In this task, you will classify 400 movie reviews by whether they are positive or negative; that is, by whether the reviewer liked or disliked the movie. This task will take around half an hour, but could take 15 minutes more or less depending on your motivation and speed.

Reviews that have been classified into positive or negative by hand are an important input for training computer algorithms (see, e.g., https://en.wikipedia.org/wiki/Labeled_data).

Please give it a try!
You do NOT need to complete it, just try it for a bit so you know how much / how little you like it)
Once you're done, click the next button.

The counter on top shows you the number of reviews you have classified correctly. For each correctly classified review, the counter increases by 1, but for each mistake you make, the counter decreases by 1.

Reviews classified correctly: 0

```
This film is overblown, predictable,
pretentious, and hollow to its core. The
settings are faithful to the era but self-
conscious in their magnification by prolonged
exposure. The lingering over artifacts stops the
action and cloys almost as much as the empty
dialogue. Tom Hanks seems to be sleepwalking
much as Bruce Willis did in Hart's War. Tom, you
can't give depth to a character simply by making
your face blank! The content did not warrant the
histrionic acting by Paul Newman. This is a dud
wrapped in an atomic bomb casing.
```

POSITIVE NEGATIVE

Spoken Words Transcription (task 2)

In this task, you will hear 400 spoken words. For each of them, you will click a button to indicate what was said. Transcribing spoken words takes few special Workers with experience in audio-transcription will typically require about 15 minutes to transcribe the text, whereas workers with less experience may take a bit longer.

Transcribing spoken text is needed as computers can readily analyze written data, but often have trouble with spoken words.

Please give it a try!
You do NOT need to complete it, just try it for a bit so you know how much / how little you like it)
Once you're done, click the next button.

The counter on top shows you the number of words you have transcribed correctly. For each correctly transcribed word, the counter increases by 1, but for each mistake you make, the counter decreases by 1.

Words transcribed correctly: 1

-0:01

BED CAT DOG DOWN GO HAPPY
HOUSE SEVEN UP YES

Image Labeling (task 3)

In this task, you will see a sequence of 400 images. For each image you will click a button to indicate the content of the image. Labeling images does not take any special skills, and can easily be done while listening to music. This task will take about half an hour but could take 15 minutes more or less depending on your speed.

Images whose content has been indicated by hand are an important input for training computer algorithms (see, e.g., https://en.wikipedia.org/wiki/Labeled_data).

Please give it a try!
You do NOT need to complete it, just try it for a bit so you know how much / how little you like it)
Once you're done, click the next button.

The counter on top shows you the number of images you have labeled correctly. For each correctly labeled image, the counter increases by 1, but for each mistake you make, the counter decreases by 1.

Images labeled correctly: 0

Plane Car
Cat Bird
Deer Dog
Frog Ship
Horse Truck

Twitter hate speech sorting (task 4)

In this task, you will sort 400 short messages posted on twitter.com by whether they include hate speech (e.g. racist or sexist statements). This task will take around half an hour, but could take 15 minutes more or less depending on your motivation and speed.

Some workers may find this task emotionally taxing, other workers may not be bothered.

Messages that have been hand-classified into offensive and harmless are an important input for training computer algorithms to automatically detect offensive messages (see, e.g., https://en.wikipedia.org/wiki/Labeled_data).

Please give it a try!
You do NOT need to complete it, just try it for a bit so you know how much / how little you like it)
Once you're done, click the next button.

The counter on top shows you the number of messages you have classified correctly. For each correctly classified message, the counter increases by 1, but for each mistake you make, the counter decreases by 1.

Classified correctly: 0

VONtEthekIDd
@_Vontethekidd

#CareerArc #Hospitality #Job alert: Barista (US) | Starbucks | https://t.co/XZNA7otEqp #Veterans #Jobs #Hiring

HATE SPEECH | CLEAN

←

Assigning apprentices to mentors (task 5)

This task requires more thought than the others. If you complete this task, you will repeatedly assign each of five (hypothetical) apprentices at a (hypothetical) company to one of five (hypothetical) mentors at that company.

You will have to create such assignments for 20 companies. This task will take around half an hour, but could take 15 minutes more or less.

You cannot just create any arbitrary assignment. Instead, each of the apprentices have indicated which mentor they would prefer most, second most, and so on. Likewise, each of the mentors have indicated which of the apprentices they would most like to mentor, which they would second-most like to mentor, and so on. You will need to find a way to pair apprentices and mentors to make all apprentices and mentors as happy as possible. (Specifically, you will have to find an assignment in which there are no two people that are not paired with each other, but would prefer each other over their assigned partners.)

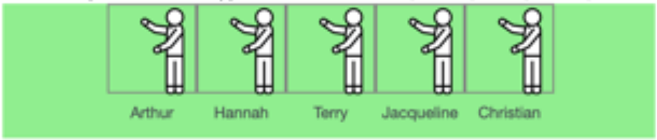
You will have to create such assignments for 20 companies.

Some people will find this task more engaging than the less challenging tasks, while others will be put off by it. Some people will be much better at this task than others.

Please give this task a try. (You do NOT need to complete it, just try it for a bit so you know how much / how little you like it)

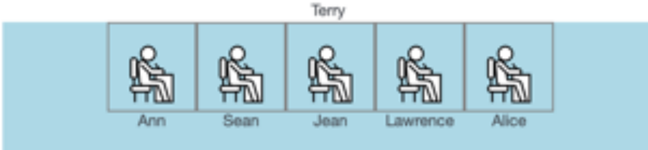
Mentors

Arthur's preferences over apprentices are 1. Lawrence, 2. Alice, 3. Sean, 4. Jean, 5. Ann
Hannah's preferences over apprentices are 1. Ann, 2. Sean, 3. Lawrence, 4. Alice, 5. Jean
Terry's preferences over apprentices are 1. Lawrence, 2. Sean, 3. Alice, 4. Ann, 5. Jean
Jacqueline's preferences over apprentices are 1. Lawrence, 2. Alice, 3. Jean, 4. Ann, 5. Sean
Christian's preferences over apprentices are 1. Lawrence, 2. Jean, 3. Ann, 4. Sean, 5. Alice



Apprentices

Ann's preferences over mentors are 1. Hannah, 2. Arthur, 3. Terry, 4. Christian, 5. Jacqueline
Sean's preferences over mentors are 1. Christian, 2. Jacqueline, 3. Hannah, 4. Arthur, 5. Terry
Jean's preferences over mentors are 1. Terry, 2. Christian, 3. Arthur, 4. Hannah, 5. Jacqueline
Lawrence's preferences over mentors are 1. Terry, 2. Jacqueline, 3. Arthur, 4. Christian, 5. Hannah
Alice's preferences over mentors are 1. Jacqueline, 2. Hannah, 3. Christian, 4. Arthur, 5. Terry



Pair mentors and apprentices

Drag and dropping them into the boxes below.

CHECK ANSWER

← →

Your decisions

Today's part of the experiment consists of a single decision.

At the beginning of this study, the computer has randomly selected one of the rounds. There is a 5% chance that your choice in that round will determine which of the tasks you will complete in part 2 of this study according to a procedure we will describe shortly. (With the remaining chance, the task you complete in part 2 will be determined in a different way.)

→

Your decisions

Today's part of the experiment consists of a single decision.

Your task is to rank the five work tasks in the order that you genuinely prefer. Put the task you like most on top, the task you like second-most in second place, and so on. The task you like least will be on the bottom.

Our study is designed so that it is in your own best interest to rank the tasks as you genuinely prefer.

Here's why. At the beginning of the study, the computer has selected at random two possible tasks for you out of the five. There is a 5% chance that your choice in that round will determine which of the tasks you will complete in part 2 of this study according to a procedure we will describe shortly. (With the remaining chance, the task you complete in part 2 will be determined in a different way.) If your choice determines the task you will complete in the second part of the study, you will complete the one you have ranked more highly out of these two.

← →

Your choice

Please rank the five tasks in the order of your preference, as explained on the previous page.

Put the most preferred task on top, and the least preferred on the bottom.

↑

more preferred

Spoken word transcription (400 words)

Movie reviews classification (400 reviews)

Twitter hate-speech filtering (400 tweets)

Assigning apprentices to mentors (20 matchings to be found)

Image labeling (400 images)

less preferred

↓

← →

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Other (e.g. genderqueer)

What is your age?

- ◯ Under 18
- ◯ 18 - 24
- ◯ 25 - 34
- ◯ 35 - 44
- ◯ 45 - 54
- ◯ 55 - 64
- ◯ 65 - 74
- ◯ 75 - 84
- ◯ 85 or older

← →

This is the end of the first part this study.

We will invite you for the second part of this study in one to four weeks.

We will send you the link through the text field for a small bonus payment. Hence, please make sure to follow your bonus payments.

Please enter

HFB847IN

as the survey code and submit the HIT.

Thank you for your participation.

← →

E.4 Elicitation of Swiss citizen Stakeholder preferences

English translation

Q1. Good day! Are you a citizen Of Switzerland? [Yes / No]

Q2. What is your general political attitude? [Clearly right, moderately right, center, moderately left clearly left]

Q3. This study is about a donation of SFr. 30 to one of the five largest Swiss political parties (measured by percentage of seats in the National Council). Your answer, as well as the answer of five other study participants will determine which party receives the donation.

Q4. With a one in forty chance, your answer will completely determine which party receives the donation. With the remaining probability, your answer will partly determine the recipient.

Q5. Please indicate which party you would like the most to receive the donation, and which the least. (Choose "1" for "the most" and "2" for "the least.") The order of parties below is random. The computer has randomly selected two parties. If your own answer determines the recipient, the party (of the two) that you prefer more will receive the donation.

Original