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Methodological and Ideological Options

The importance of social learning for non-market valuation

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ABSTRACT

Neoclassical valuation methods often measure the contribution that non-market goods make to utility as income compensations. This circumvents Arrow's *impossibility* (AI) –a theoretical proof establishing the impossibility of social preferences – but those methods cannot be used in all settings. We build on Arrow's original proof, showing that with two additional axioms that allow for social learning, a second round of preference elicitation with a social announcement after the first, generates logically consistent social preferences. In short: deliberation leads to convergence. A 'web-game' aligning with this is trialed to select real world projects, in a deliberative way, with the board of an Australian Aboriginal Corporation. Analysis of the data collected in the trial validates our theory; our test for convergence is statistically significant at the 1% level. Our results also suggest complex social goods are relatively undervalued without deliberation. Most non-market valuation methods could be easily adapted to facilitate social learning.

1. Introduction

The Millennium Ecosystem Assessment emphasized the importance of properly measuring the impact of social decisions on ecosystems given their importance to human wellbeing (Bullock et al., 2018). That this notion has been widely accepted is evidenced by the rapid growth in studies that seek to do that – often using neoclassical non-market valuation methods to generate estimates and with large organizations supporting the endeavor (see, for example, The Economics of Ecosystems and Biodiversity (Braat and De Groot, 2012)).

Neoclassical methods have done much to highlight the importance of numerous non-market goods and services, including various ecosystem services, but cannot measure the value of all goods and services (Cook et al., 2017). They are adept at measuring the value (in terms of income compensation) of simple individual goods – herein denoted as SIG and defined as a good that generates a simple/singular benefit (e.g. more income or more food) which accrues to an individual, but struggle to adequately measure relational values (Chan et al., 2016), with some arguing that neoclassical methods are, by definition, incommensurable with them (Kallis et al., 2013; Oberheim and Hoyningen-Huene, 2009).[1] Neoclassical methods are not yet adept at measuring the value of complex social goods (Stoeckl et al., 2018) – herein denoted CSG and defined as goods that generate a diverse range of benefits[2] that accrue to a diverse range of people at multiple social scales (e.g. to individuals, families, communities and/or society more broadly). This is because neoclassical methods are essentially partial equilibrium in nature – specifically designed to assess the value of singular/simple goods that generate benefits for individuals, whilst assuming all else is constant (and that individual preferences/utility functions, are independent). The social valuation of ecosystem services (particularly those that are essentially CSGs), which allows one to deduce social preference, thus remains an open problem for contemporary ecological economics (Kenter et al., 2015; Kenter et al., 2016).

Social and individual preference are context dependent (Tversky and Simonson, 1993; Chan et al., 2016; Hansjürgens et al., 2017), have plurality of values (Himes and Muraca, 2018; Rawluk et al., 2019) and align with non-anthropocentric ideals (Batavia and Nelson, 2017). Importantly, having a plurality of value means that different things of value elicit different responses in individuals that sit within a socially constructed context (Tadaki et al., 2017). Likewise, Kuhn's monist emphasis at the individual level aggregates to plurality at the social level (Šešelja and Strasse, 2013). For example, making eye contact may be seen in a plural way across individuals. It may be conceived as respectful or aggressive depending on the social context. This means that the value an individual places on a good or service when asked to consider only their own personal preferences may be quite different

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[1] This begs the question as to whether relational values can be measured at all BOURKE, J. E. 2010. Incommensurability and Deliberation: Prolegomena to Pluralist Politics. *In Western Political Science Association 2010 Annual Meeting Paper.*– although Schulz and Martin-Ortega (2018) offer an alternate view.

[2] These could, but will not necessarily, include relational values.

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from the value they place on that good or service if asked to consider the views of (or for) a group (Arias-Arévalo et al., 2018); and preferences that apply for one group may differ from preferences that are appropriate for another.

Neoclassical non-market valuation methods are proficient at measuring value from the perspective of an individual, but deliberative processes (Hansjürgens et al. (2017); Himes and Muraca (2018)) and group learning (Sagoff, 1998) are thought to be better suited to the task of assessing social/collective values. Importantly, Sagoff (1998) provides examples of cases where contingent valuation has been erroneously applied. Some consider there to be a lack of theoretical underpinning for deliberative valuation (Bunse et al., 2015) – an issue addressed in this paper. Deliberative approaches attempt to elicit social values by explicitly encouraging discussion amongst individuals (Kenter et al., 2015). In practice this can take the form of an initial elicitation, a follow-up discussion amongst individuals and a final elicitation used to inform the valuation (Hansjürgens et al., 2017). The deliberations thus provide a mechanism to reveal values that explicitly account for connections between people and assets (Himes and Muraca, 2018; Chan et al., 2018).

Many deliberative approaches (termed deliberative *valuations, by* Hansjürgens et al. (2017)) elicit preferences as income compensations – e.g. as willingness to pay – and thus approach the valuation task from an essentially neoclassical economics standpoint. However, whilst monetization informs social decision-making and allows one to incorporate values using cost benefit analysis (CBA), it is *Taboo* to trade-off some values in monetary terms (Kallis et al., 2013; Daw et al., 2015), commoditizing ecosystem services can lead to a long-term problems for biodiversity conservation (Gómez-Baggethun and Ruiz-Pérez, 2011) and over-reliance on monetized values can contribute to the crowding out of CSGs (Stoeckl et al., 2018). Deliberative approaches which elicit preferences in other ways, termed deliberative *institutions, by* Hansjürgens et al. (2017), thus offer themselves as an attractive alternative in some settings.

Methods which seek to identify social preferences by first asking individuals to rank preferences (without using money as a metric), and second aggregating individual preferences to generate a social ordering, are, however, vulnerable to criticism by neoclassical economists on (Arrow's) theoretical grounds (Kenter et al., 2015). Crucially, CBA and related non-market valuation methods that capture preferences in terms of income compensations do not require one to directly measure social welfare (instead only asking if changes will improve it). As such, they circumvent Arrow's *impossibility (AI)* the name used for a theoretical 'proof' that it may be impossible to derive logically consistent social preferences directly, e.g. with voting (Arrow, 1950).

It is nowadays widely accepted that AI holds in some situations, but not all (formally, if one restricts individual preferences to ensure it is possible to maintain logical consistency when aggregating individual preferences to a social order (Sen, 1977)). However related 'solutions' to AI involve excising potentially problematic individual preferences (Sen, 1999; Inada, 1969). This is computationally intractable for a large number of goods and individuals, limiting the usefulness of these 'solutions' in real world settings. The lingering shadow of AI thus makes it difficult for approaches that do not measure values using money as a metric to gain traction as rigorous alternatives to the norm. In this paper, we seek to redress that problem.

In Section 2 we provide a proof that deliberative methods, which incorporate 'social learning', do not suffer from AI and are thus theoretically sound – even if preferences are only measured using ratings and rankings (rather than income compensations). A real world application of this validates our theory in Section 3, whilst Section 4 discusses the implications of our work and related tasks for future work. Our brief conclusion provides key takeaway messages. Supplementary materials, including a brief review of historically relevant literature, provide information for readers interested in further details.

2. Theoretical background

2.1. The original Arrow proof

Arrow (1950) identified six conditions (axioms) that describe individual and social preferences:

1. If something is preferred to something else it will still be preferred to something else if it increases in value (*more is always better*),
2. Something is preferred to something else independent of another different thing being present or not (*Independence of Irrelevant Alternatives IIA*),
3. Any individual preferences are possible (*Universality*),
4. There does not exist a dictator (i.e. *no person or policy dictates the social preferences*), and
5. If all individuals prefer something to something else then the social preference also prefers it (*unanimity*).
6. If a good A is preferred to a good B and a good B preferred to a good C, then good A is preferred to good C (*transitivity*).

Utilizing these axioms the AI proof is summarized as follows. Let there be 2 individuals with individual preference relations P_1 and P_2 that aggregate into either strict social preference P (i.e. by unanimity axiom xP_1y *and* xP_2y *implies* xPy meaning if both individuals prefer x to y then the social preference prefers x to y; N.B. that IIA is implicit given that this is independent of z per the above assumption), or indifferent social preference I (i.e. by no dictator axiom yP_1x and xP_2y implies xIy, N.B. neither individuals 1 or 2 is a dictator of the social preference given the indifferent social preference) but not both I and P are permitted to hold simultaneously (i.e. a social preference can't be indifferent and also strictly prefer at the same time), for three goods x, y, z.

Suppose individual 1 has preference ordering xP_1yP_1z and individual 2 has ordering zP_2xP_2y (N.B. these and other preference orders are allowed because of the universality axiom). Given xP_1y and xP_2y then xPy must holds by transitivity. Given yP_1z *and* zP_2y then yIz by non-dictatorship. Therefore, xPy and yIz implies xPz by the transitivity axiom. But xP_1z and zP_2x implies xIz by the non-dictator axiom. Therefore, xPz and xIz holds simultaneously; which contradicts what is permitted. Hence, no logically consistent social preference satisfying all 6 conditions holds in general (without leading to a logical contradiction).

2.2. A two round Arrow (1950) setup with social learning

Arrow (1950) clearly describes a one round social selection setup i.e. "…[individual preferences are only elicited] once for all and then [a social benefactor aggregates individual preference and] chooses [the best social preference] …". His individuals do not interact, so his set-up implicitly precludes social learning; it also (implicitly) assumes that either altruism does not exist, or that if altruism does exist, perfect information is present[3] (with all individual's aware of, and already account for, the preferences of others). If *altruism* and *imperfect information* co-exist then, a one-off elicitation process cannot identify social preferences. So what would a two round Arrow (1950) setup with social learning look like?

AI can result from cyclic social strict preference transitivity i.e. x is preferred to y which is preferred to z which is preferred to x. So to identify logically consistent social preferences, one must at least avoid cyclic transitivity. Black (1948) suggested that this could be achieved through (possibly) multiple rounds of motions of committees to achieve

[3] Imperfect information is present if individual A is initially unaware of individual B's preferences CROSON, R. 1996. Information in ultimatum games: An experimental study. *Journal of Economic Behavior & Organization,* 30, 197.

the goal of (single peaked) *majority rule*. But that approach has been shown to fail (in, for example, the Borda and Condorcet approaches (Miller, 2017) except when only assessing two candidates (May, 1952; May, 1953)). We set a similar, but subtly different goal of *consensus*, showing that consensus is associated with logically consistent social preferences and obtainable in just two-rounds. The proofs invoke the set theoretic analog of the pivotal Grainger et al. (2015) "learning" and "equilibrium" axioms. Instead of the calculus of Grainger et al. (2015), the more general set theory notation is used and its generality makes it more powerful.

2.2.1. Theorem for the two round setup

The following deliberately uses the same set theory notation that Arrow (1950) employs. It is important to note that indifference, weak and strong preferences having a specific meaning that is close but not identical to common usage. This approach is taken in order to show AI may be circumvented without abandoning Arrow's nomenclature. The key idea is that AI still exists in the first round, but is resolved in the second round of a particular 2 round model.

Let $xp_i^n y$ denote that, in round n, individual i is either indifferent or prefers x to y. It is said that x is weakly preferred to y by individual i in round n.

Let $xP_i^n y$ denote that, in round n, individual i is not indifferent and prefers x to y. It is said that x is strictly preferred to y by individual i in round n.

Let $xp_S^n y$ denote that, in round n, society S is either indifferent or prefers x to y. It is said that x is weakly preferred to y by society S in round n.

Let $xP_S^n y$ denote that, in round n, society S is not indifferent and prefers x to y. It is said that x is strictly preferred to y by society S in round n.

Let Arrow (1950) axioms hold in two rounds.

Add to the other Arrow (1950) axioms the two following axioms:

Axiom of Learning (AL): if society strictly prefers x to y in the first round, then all individuals will weakly prefer x to y in the second round i.e. a strict first round preference means learning from the first round social announcement (strict preference) may take place. Formally, $xP_S^1 y$ implies $xp_i^2 y$ for all i.

Axiom of Equilibrium (AE): if society weakly prefers x to y in the second round, then it must be the case that society strictly preferred x to y in the first round i.e. a second round weak social preference at the very least requires a strong first round social announcement (strict preference). Formally, $xp_S^2 y$ implies $xP_S^1 y$.

In short, these two additional axioms added to a two round Arrow (1950) setup is a reasonable and arguably conservative addition. They establish that AI holds in round 1 as expected with unrestricted domains. In the second round, AL and AE serve to automate a set restriction. For example, as will soon be demonstrated, because there is a second round consensus the no dictator axiom presents no problem given one person does not govern all persons.

2.2.1.1. Why not something other than AE and AL?

Looking at the opposite of the logical axioms helps to justify them. Consider the logical negation of the AE implication here to see this i.e. what one might not believe is that equilibrium is defined by "both $yP_S^2 x$ and $xP_S^1 y$ are true". This does not reflect the notion of equilibrium – hence AE seems reasonable.

The logical negation of AL is also hard to believe i.e. $yp_S^1 x$ and $xp_i^2 y$ for all i hold. That is, the negation of AL is saying that a weak social preference in the first round and a second round consensus in opposition to it holds. No learning takes place for a first round weak social preference does not appear to align with the concept of learning – hence AL seems reasonable.

In short, logical negation offers a guide to what AE and AL axioms should *not* be. Specifically, you would not likely want the above negations to represent AE and AL. Moreover, you would likely wish for the opposite of those negations. In this light, AL and AE as defined in this paper seem to be reasonable axioms. However, as in Arrow (1950) they are debatable e.g. Arrow's Independence of Irrelevant Alternatives (Colignatus, 2008).

2.2.1.2. Imperfect information and altruism

'Learning' implies that (a) imperfect information is present in round one; and (b) when information is updated, people update their preferences to better align with social preferences. This also assumes altruism is present.

AL defines social learning in the syntax (formalism) of axioms – but semantically (meaning) is that one has imperfect information and learns altruistically from the social announcement. This results in second round individual preferences aligned with the first round social announcement. In contrast to other deliberative approaches allowing complex multiple social interactions (Orchard-Webb et al., 2016), a single social announcement (deliberately simple setup) is assumed here. For example rebellion is not modeled here, as it would introduce axioms for complex strategic play (Chen et al., 2007); where some individuals can oppose prior social announcements. Ultimately, the empirical application described in Section 3 provides a good test of the simple theory of this paper, and a good test for whether altruism (or rebellion) exists. This study finds evidence of altruism in line with other research – see, for example the related ultimatum and dictator games (Camerer and Thaler, 1995).

2.2.1.3. The theorem & proof

2.2.1.3.1. Theorem. Consensus across individuals is a sufficient and necessary condition for logically consistent social preferences in the second round.

2.2.1.3.2. Proof. The focus here is on a set of goods that may be ranked by individual or social preferences.

The seminal proof of Arrow (1950) considered > 2 goods with > 1 individual. The following considers the same. That is, given > 2 goods and > 1 individual in a society, the following holds; given Arrow's axioms, AL, AE and the usual rules of set theory.

In the first round AI holds as usual. Arrow used a reductio ad absurdum proof i.e. he assumed the opposite of the statement "social preferences in the first round are logically consistent" is true and if a contradiction is reached then the statement must be true.

The crux of the current proof also utilizes a reductio ad absurdum proof. Specifically, if one assumes that "social preferences in the second round are not logically consistent" a contradiction is reached, and therefore logically consistent social preferences must exist in this two round setup.

In the second round social learning occurs to circumvent AI as follows.

AE ($xp_S^2 y$ implies $xP_S^1 y$) and AL ($xP_S^1 y$ implies $xp_i^2 y$ for all i) result in $xp_S^2 y$ implies $xp_i^2 y$ for all i (i.e. consensus is a necessary condition). Then $xp_i^2 y$ for all i implies $xp_S^2 y$ by the axiom of unanimity (i.e. consensus is a sufficient condition).

Now assume "social preferences in the second round are not logically consistent". This means that there must be at least two goods x, y such that $yP_S^2 x$ and $xp_S^2 y$ i.e. the social preference is not logically consistent because they contradict one another. But this is not possible because of the following.

Starting with $xp_S^2 y$ and using the usual rules of logical deduction means a contradiction is reached whereby $yP_S^2 x$ is false. Hence the assumption is false and "social preferences in the second round are logically consistent".

Starting with $xp_S^2 y$ then implies $xP_S^1 y$ by AE, which implies $xp_i^2 y$ for all i by AL, which implies $xp_S^2 y$ by AU, which contradicts with the assumption $yP_S^2 x$. Therefore, a contradiction has been reached, and it must be the case that "social preferences in the second round are logically consistent". **QED.**

Table 1
Summary of projects with details of good, round one and round two mean and standard deviation of guesses – deeper analysis required.

Name	Nominated by	Type of good	Round 1 mean guess	Round 1 standard deviation	Round 2 mean guess	Round 2 standard deviation
More Ewamian Land Management Programs	Researchers	CSG	86%	14%	89%	10%
Electricity House Rebate $20 per Week	Researchers	SIG	58%	20%	71%	23%
Govt Increasing PBC Board and Employee Payments	Researchers	SIG	61%	23%	71%	16%
Build Solar Farm Talaroo	Board	CSG	92%	11%	93%	13%
Ewamian Enterprise Artifact Making	Board	CSG	77%	13%	84%	12%
Housing On Country	Board	CSG	79%	17%	89%	9%
Do Something Else	Researchers	CSG or SIG	58%	15%	67%	13%

2.2.2. Real world predictions motivated by the theorem

The theorem uses the same fundamental nomenclature as Arrow (1950) with metamathematical adaptations that are not atypical (Mihara, 1997). For example, the preference relation nomenclature has been modified to reflect rounds. Importantly, rounds are connected by AL and AE axioms. Ultimately, the theorem suggests that, in the second round, a consensus is reached and logically consistent social preferences hold. This implies two real world predictions for such a system:

1) Convergence to a consensus occurs from round 1 to round 2 - a direct statement of the theorem.
2) CSGs are more affected by social announcements than SIGs - given the presence of social learning.

Convergence to a logically consistent social preference consensus becomes probable (rather than certain) in the real world. Therefore, real world empirical testing of the theoretical predictions is desirable.

3. Empirical application

3.1. Overview

The board of an (Australian) Aboriginal Corporation (the Ewamian Aboriginal Corporation (EAC)) participated in the application of the theory – EAC being charged with determining which of numerous complex projects and programs are likely to best serve the needs of their community. Hence, EAC was considered a suitable context to implement a version of the real world web-app of the Grainger et al. (2015) decision market game aligned to the aforementioned theory. The dynamics observed in this real world social settings are not expected to identically mimic the theorem (in Section 2.2), but the theory proposed in this paper can be validated via testing the two (theorem implied) predictions. To this end, data collected during the live EAC 'game' (using the tool) was used to test the predictions. This empirical data was then used to generate an estimate of the valuation of the diverse projects considered in the game by EAC.

3.2. Decision-making context & justification as case study to test theory

3.2.1. Background

The web-app designed by Grainger et al. (2015) was adjusted for use with eight board members of EAC. The Ewamian people have traditional lands in the Einasleigh Uplands region, inland from Cairns, in North Eastern Australia. They were disposed of their lands in the late 19th century through European colonization and government policies. Although many Ewamian people remained in areas near their traditional lands, many were forcibly transported to other regions and living near traditional lands surrounding Atherton/Mareeba/Cairns and also around Brisbane and Cherbourg. The EAC was registered as a Prescribed Body Corporate (PBC) in 1994, to support an application for Native Title. They were successful and were granted Native Title over > 29,000 km^2 of Ewamian land part of which was declared as an Indigenous Protected Area (IPA) of Australia's National Reserve System.

3.2.2. Justification as case study to test theory

The principal objective of the EAC is social – the board's aim being to make decisions that improve the (social) welfare of Ewamian people – wherever they may live. The Ewamian board is thus a particularly good setting in which to trial the proposed method for identifying logically consistent social preferences for environmental and other goods/services. Ultimately, EAC board, each having individual and social interests, deliberates to identify a ranking of CSGs to the benefit of Ewamian. Hence the theoretical setup agrees well with the EAC context. EAC as a research partner agreed to use the web-app willingly; all well knowing it was a web-app under test. As such, EAC was a logical opportunity for this research.

3.3. Methods

The following method is not unlike the market stall deliberative approach (Hansjürgens et al., 2017). An important difference lies in the use of a social announcement (via the web tool), rather than a social discussion of willingness to pay. The social announcement is utilized as it aligns directly with the theory proposed (in Section 2.2). A social announcement simplifies the logical proofs; as is typically done in information market literature (Chen et al., 2004; Grainger et al., 2015). One can see, in contrast, multiple interactions complicate the setting. The algorithms that ensure logically consistent aggregation were provided in Grainger et al. (2015) and Grainger (2017).

EAC board members were asked to rank 7 diverse projects relevant to their people. All goods may be seen as both individual and social – each good being somewhere on a spectrum between these extremes. Some of the projects could easily be considered a *CSG* (e.g. supporting Indigenous land management (ranger) programs on their Indigenous Protected Area), and some better described as *SIGs* (e.g. Board pay increases and electricity rebates). Projects and their assignment to CSG, SIG or both are listed in Table 1; where the Board nominated projects 4, 5 and 6 and the researchers nominated the remainder.

The game was designed to allow for multiple rounds interspersed with a 'social announcement (Grainger, 2017); also called a score. However, when implemented, there was rapid convergence by the second round (see Section 3.4.2), so participants were not asked to continue beyond round two. The first round required the board members to provide (secret) individual assessments (votes/guesses) of the desirability of each project. They were asked to 'guess' the likelihood that each project would, when all assessments were considered together, be rated as one of the best projects for the Community. Each Board member was provided with an individual 'voting sheet' that listed all seven projects, and asked to allocate each a mark on a scale from 0 to 10; whereby 10 represented the highest chance of a project being picked by the Board. This aligns with the concept of common knowledge i.e. each person bases their decisions on what they think others think that they… etc. (Aumann, 1976). Such a setup is simply an aggregation of information – they are in fact equivalent to attaining the best possible prediction/decision as mentioned in Grainger et al. (2015).

The decision-market algorithm described in Grainger et al. (2015) was implemented in the game and used to aggregate guesses into a score, and to also allocate rewards to board members: the closer their guess was to the score, the higher their reward.[4] Use of rewards in this way, is in line with other applications in information markets and has been shown to ensure that final outcomes aligns with the best possible decisions (Grainger et al., 2015; Grainger, 2017). At the end of the first round the project scores and rewards for board members were shared with all on a scoreboard. This served as the end of round 1 social announcement. The Board was then asked to re-assess the projects in a second (final) round in light of the social announcement (scores). This provided each individual with the opportunity to update their previous guesses if they so wished. The tool/game was used to update social preferences/scores, with final results shared and discussed with the board.

Analysis of data collected in the game to test predictions (1) and (2) was performed. The means and standard deviations of all guesses for all projects and both rounds are reported. This motivated deeper statistical analysis. As such, the theoretical prediction of convergence to unanimity can be tested for using the definition of "distance". Distance here is formally defined as the absolute difference between the individual guess and the average guess (across all participants and projects) in a round. In this way, distance is a function of rounds and independent of projects and individuals. If rounds increase and distance decreases, then convergence is said to be occurring from round 1 to round 2 (prediction 1). The test for convergence utilized a logit regression of the binary response variable for round R (whereby 0 denotes round 1 and 1 denotes rounds subsequent to round 1) on the explanatory variable for distance D (of the individual guess from the mean guess for the round) and the control function residual $e(D)$ (used to control for confounding and endogeneity (Lewbel et al., 2012; Dong and Lewbel, 2015)).

The theoretical prediction of CSGs being differently affected, by the social announcement, than SIGs (prediction 2), is also testable with the "distance" concept. Convergence being larger for CSGs than for SIGs was tested. Here too, a logit regression was used for the binary response variable for CSG status S (whereby 1 denotes a CSG and 0 denotes a simple individual good) on the explanatory variable for distance D individual guess from the mean guess for the round and the control function residual $e(D)$ (Lewbel et al., 2012; Dong and Lewbel, 2015). The theoretical prediction of the link between guesses, CSGs, and rounds was also tested. Because the guesses in the game are bounded between 0 and 1, the log odds of the guesses are regressed onto CSGs and rounds.

Given that the scoreboard provides an incentive compatible best possible prediction, it is used to generate an estimate of the 'value' of each project (Grainger, 2017). A suitable payment vehicle that is familiar to participants is used to do so (Cook et al., 2018). A typical single round valuation (using the means of guesses) is also performed and compared to the valuation generated using the scoreboard.[5] Analysis suggests that typical valuation leads to greater undervaluation of CSGs than SIGs.

[4] The score and rewards makes guesses incentive compatible i. e. individuals maximize their chance of reward when they submit truthful guesses informed by the latest score (information). The score is then updated to reflect all relevant information needed for the next round of guesses i.e. the score is a best possible prediction.

[5] In the game, scores provide a best possible (probability) prediction and guesses act like bids. Maximizing the entropy of the "product of bid, probability and scaling factor" implies an optimum at which the "product of bid and probability" is a constant. This then implies that valuations derived using a ratio of probabilities are the same as those using the reciprocal of the ratio of bids.

3.4. Results

3.4.1. Observations summarized and justifying further analysis

Due to the sensitive nature of the EAC game data, the guesses provided by each individual participant are only attainable by request conditioned upon authorized release. However, a summary of information relating to respondent guesses for each project across both rounds is presented in Table 1. The mean values of guesses for each project appear to increase from round 1 to round 2. The associated standard deviations appear to decrease from round 1 to round 2. Taken together, Table 1 is suggestive of convergence from below. However, deeper statistical analysis needs to be performed on the raw game data to determine this; particularly given the variation in standard deviations in Table 1. This is undertaken in Tables 2 to 4 and depicts convergence to a consensus from rounds 1 to 2 at a 1% significance level, and greater undervaluation of CSGs than SIGs at a 5% significance level. Table 5 allows us to assess the empirical extent of the undervaluation.

3.4.2. Tests for convergence

Table 2 shows results from the logit regression of round (R) on distance (D) (of individual guesses) from mean (of guesses across all respondents) – the test of prediction 1. These results suggest that the distance of a player's guess from the mean decreases from round 1 to round 2. Specifically, the coefficient of D being negative, suggests that as distance decreases the chance of being in a round after the first round increases. That is, convergence to unanimity is likely occurring from round 1 to round 2 in a statistically significant way as predicted by theory, for all goods. The control function properly produces a clean error; and was required as it indicates the presence of endogeneity and confounding. The large coefficient for distance suggests that convergence for all goods is rapid. In addition, the Board discussed and agreed with the round 2 rankings (of Table 1) when asked i.e. a consensus appeared to have been formed by the end of round 2; adding to the confirmation of theory.

3.4.3. Tests for differences between simple individual and complex social goods

Table 3 shows results relevant to prediction two, undertaken using a logit regression of CSG status (*CSG)* on distance D. Evidently, an increase in distance corresponds to a decrease in the probability of the good being a complex social one. The control function produced a clean error in the presence of detected confounding and endogeneity. The analysis underpinning results from Table 2 validates convergence from round 1 to round 2 for all goods. This additional analysis shows that, when both types of goods converge to a similar region around the mean, then CSGs converge from a greater distance. Specifically, blind individual guesses (distances) which do not adequately capture benefits that accrue to others (the community more broadly) occur in round 1. It is round 2 that demarcates CSGs and SIGs; arguably because of the different way people respond to social announcements. The information embedded within the social announcement thus has less impact on assessments of SIGs than on CSGs – as we have defined them. We note that different definitions, or similar definitions in different contexts, would generate different results. Although subject to empirical testing, we suggest that the general finding, that CSGs are undervalued by individualistic assessment methods is likely to hold. We also note, in this application, CSGs show a significantly greater rate of convergence than SIGs.

Further investigation into the nature of CSGs, relative to SIGs, is represented in the regression of Table 4. It demonstrates that, all else being equal, CSGs status contributes to the individual guess of a project at < 1% statistical significance level. In short, statistical analysis demonstrates it is highly unlikely that there is no difference between SIGs and CSGs.

Table 2
Logit regression of Round on Distance from mean guess.

R	Coefficient	Std. error	p-Value
D	−36.7	6.6	0.00
e(*D*)	37.7	6.7	0.00
Constant	5.9	1.0	0.00
Observations = 140			
LLR = 55.09			

Table 3
Logit regression of CSG on Distance from mean guess.

CS	Coefficient	Std. error	p-Value
D	−12.4	4.3	0.00
e(*D*)	10.8	4.8	0.02
Constant	2.9	0.7	0.00
Observations = 140			
LLR = 10.2			

Table 4
Linear regression of the log odds of the individual guess (L) on CSG status (CSG) and round (R).

L	Coefficient	Std. error	p-Value
CSG	1.0	0.2	0.00
R	0.6	0.2	0.00
e(*CSG*)	−1.4	0.4	0.00
e(*R*)	−1.1	0.5	0.03
Constant	1.0	0.3	0.00
Observations = 110			
F(4, 105) =12.33			

for the particular score distribution is used to estimate the lower and upper bound score-derived valuation in Table 5. Given the probability density function is complex, this was undertaken by applying the Tchebychev inequality to the score algorithm to arrive at:

$$P\left[|x - p_n| < \left|\frac{20p_n^2(r_n - r_1)}{r_n n(n-1)}\right|\right] > 99\%$$

where x is a point, p_n the mean, r relevant information level, n number of guesses .

This simply means that irrespective of the functional form of the probability distribution, a point estimate is rejected at a 1% significance level if it lies > 10 standard deviations from the mean of the probability distribution.

Table 5 depicts the lower and upper bounds of the score distribution at a distance of 10 standard deviations from the mean. Any point estimate outside of the lower-upper region is rejected at the 1% significance level. Rather than working with scores, we look at the ratio of the simple mean of round 1 guesses (relative to the monetary numeraire) to draw inferences about the values that would obtain in a single-round study. With the exception of "Do something else" all mean values derived from this simple valuation approach are statistically different from the values generated using round two scores at the 1% level. That is, the typical 1 round valuation undervalues all goods.

In addition, Table 5 shows that mean values associated with CSGs, derived from second round scores are almost double the value estimates derived from the first-round 'guesses'; the differences in values for SIGs are much smaller.. This is pima-facie suggestive of greater undervaluation of CSGs than SIGs. More formally, a *t*-test performed on the lower bound score-derived valuation and the typical round 1 mean guesses derived valuation finds that the latter is undervalued at a 1% significance level. A simple logit regression of CSG status on the valuations identifies threshold values exist below which all goods are CSG. Combining these insights with the previous analysis, a typical single round valuation undervalues CSGs more than SIGs. This bias would lead to the crowding out of CSGs if decisions were only informed by single-round valuation exercises.

Table 5
Non-market valuation range (denoted in $).

Name	Round 2 Scores	Lower $ (using scores)	Mean $ (using scores)	Upper $ (using scores)	$ (estimated from round 1 mean guesses)
More Ewamian Land Management Programs - CSG	91%	$24.08	$24.46	$24.86	$13.45
Electricity House Rebate $20 per Week - SIG	75%	$20.00	$20.00	$20.00	$20.00
Govt Increasing PBC Board and Employee Payments - SIG	78%	$20.72	$20.87	$21.02	$18.97
Build Solar Farm Talaroo - CSG	96%	$25.39	$25.66	$25.93	$12.48
Ewamian Enterprise Artifact Making - CSG	86%	$22.98	$23.03	$23.07	$14.93
Housing On Country - CSG	90%	$23.67	$24.03	$24.40	$14.51
Do Something Else – CSG/SIG	78%	$19.76	$21.03	$22.26	$20.00

3.4.4. Valuation

It is not always appropriate to convert preferences to dollar values (Cook et al., 2018). However, we use a payment vehicle that is likely familiar to the board i.e., "Electricity House Rebate $20 per Week". In so doing, we are able to generate the valuations depicted in Table 5. A comparison is made between valuations generated using the scores in the game and more typical valuations made using single round means.

The score may be simply considered as a weighted average of individual guesses. The score is required to generate social announcements that make the game incentive compatible i.e., winning the game is aligned with the desired social objective. Specifically, these scores were generated by inputting data collected from each board member into the algorithm described in Grainger (2017). The algorithm is best described as a simple weighted average of the Shapley-Shubik kind (Grainger et al., 2015). That is, the score is a weighted average of all individual guesses made; by calculating the ratio of project specific scores to our chosen monetary 'numeraire' project ($20 per week electricity rebate), we can infer monetary values of other projects.

It is in round 2 that convergence to a consensus occurs. Therefore, a valuation range, for round 2, is of interest. A 99% confidence interval

4. Discussion

4.1. The need for a validated deliberative valuation theory

Deliberative market valuation is considered important to eliciting social preferences but lacks sufficient theoretical underpinnings (Bunse et al., 2015). Kenter (2016) issues a challenge to determine value formation from the individual level to the group level in terms of convergence or divergence. This study responds to these needs. It does this by first establishing a theory to circumvent AI. It then validates the theoretical predictions in an appropriate real world Indigenous organization.

4.2. The response to the need for a validated deliberative valuation theory

This study confirms that logically consistent social preferences are possible in a two round deliberative valuation of the type here. It also finds that CSGs are the ones most affected by (deliberative) social learning and likely undervalued if only a single round preference elicitation is utilized. This highlights the practical implications of this study: when valuing CSGs a two round deliberative approach is very likely required to appropriately inform their ranking and/or valuation. Assessments of SIGs, on the other hand, may not require a deliberative step; although caution may be required when they exhibit complex interdependencies.

4.3. Deliberative process link to information markets

Estimating the social preferences and the associated valuation of CSGs is best done using deliberative approaches – which include, but are not limited to, the web-game used in this study. See, for example, Sagoff (1998) who argues that contingent valuation studies which evolve to incorporate deliberate processes will generate better assessment than valuation tasks which do not; an argument supported by the theory and empirics of this paper. This is possibly due to deliberation creating a more democratic version of contingent valuation (Schläpfer, 2017). Contingent valuation performed in a deliberative way is a means to aggregate collective wisdom; with representativeness of the population considered important (Kenter et al., 2016). Information markets also aggregate information into best possible predictions (Chen et al., 2004). For example, the Iowa Electronic Market is an information market (Berg et al., 2008) which may be considered a deliberative process; given it aggregates collective wisdom (Brown et al., 2019).

4.4. Information markets motivate a theory for deliberative approaches

Deliberative approaches allow one to elicit individual preferences in the first round, to inform deliberation and preferences in the second round. The knowledge that is exchanged during the deliberation/interactions corrects information imperfections. This is consistent with information markets, upon which the theory of this paper is based. Concerns of plural values and incommensurability can be resolved as common knowledge lays a common foundation for comparisons to be had. The key takeaway from this study is that social preferences and valuation become logically consistent in the second round when social learning occurs.

4.5. Validating the deliberative approach theory of this paper

Whilst tested in an Indigenous context, the application of this study is broader. The web-app and deliberative approaches inform social decision-making. It sounds obvious that social decisions require a theoretical and practical setup that allows discussion about a wide range of values, criteria and objectives i.e., the sharing of information. This paper simply extends the seminal work of Arrow (1950) into a deliberative theoretical model. Using the same proof approach (reduction ad absurdum), this paper shows that a contradiction arises if one assumes it is not possible to attain a logically consistent social preference in the second round. This is theoretically proven and empirically demonstrated in this paper.

Our empirical demonstration presents both scores and valuations, which tell a consistent story. Valuation should be performed only when appropriate, with a suitable payment vehicle (that is not necessarily money), and with a deliberative (social learning) process if CSGs are being valued. In short, social learning and the incentive compatible scoring, such as the one in this study, ultimately arrives at logically consistent social preferences.

4.6. Limitations of this study

As with Arrow, the proof (in this paper) is only as strong as its axioms. However, most of the axioms utilized here are from the seminal Arrow (1950) work. Therefore they have stood the test of time. However, Arrow's single round theoretical model does not arrive at logically consistent social preferences. In contrast, our model resolves commensurability and values pluralism concerns given it does arrive at logically consistent social preferences in two rounds. Our new (AL and AE) axioms are as debatable as was Arrow's. However, they are arguably as reasonable as his. The litmus test for AL and AE reasonability performed in our study was simply to consider if these axioms were false. In so doing, unreasonable logical statements resulted. Therefore, we can say that AL and AE are not unreasonable axioms.

4.7. Practical measures for future valuation

The empirical application presented here asked participants to simply rate projects. Neoclassical non-market valuation methods could also be adapted to allow social learning and thus derive social values. For example, a standard choice modelling study could be implemented using existing rules/practices in a first round assessment. Results could be aggregated, shared and deliberated using an incentive compatible algorithm to inform a second-round assessment. Our algorithm also allows for asynchronous assessments, so if aiming to elicit preferences from a relatively large number of respondents, researchers would not need more funding to implement the study in two distinct surveys. Nowadays, many stated preference studies are implemented in an online environment. So operationally, researchers could recruit a respondent, elicit their first round preferences and inform respondent of the updated social preferences. The respondent could then immediately update their preference. Finally, logically consistent social preferences would be announced to the group to inform their priorities and valuations.

5. Conclusion

We have provided a theoretical proof that two-round preference elicitation processes incorporating social learning can lead to logically consistent social preferences. The first round exhibits AI – it is the second round (following social learning) that establishes logically consistent social preferences. In stark contrast to the one-round AI setup, social learning is implied in a deliberative process (Kenter et al., 2015), our core message being that deliberative processes are not necessarily vulnerable to AI.

We show that social learning operates to automatically restrict individual preferences to ensure second round logically consistent social preferences. This insight is also novel and markedly different to previously suggested approaches to circumventing AI which requires researchers to excise potentially problematic individual preferences (Sen, 1999; Inada, 1969). Restriction through social learning is not only more intuitively palatable but is computationally tractable (as demonstrated in our real world implementation). Importantly, our setup does not restrict the board to have purely individual or social preferences in either round – it is simply suggesting that there will be convergence to a consensus (in the maximum likelihood sense) of the social preference from round 1 to round 2.

Quantitative results from this study add weight to the theoretical foundations presented in this paper. Specifically, the theoretical predictions are validated using a (web) tool/game aligned with the theorem of this paper, and built using insights from information markets (Grainger, 2017; Grainger et al., 2015). The two theoretical predictions that follow from the theoretical proofs are empirically tested, and supported using statistical analysis of data. These were:

- Convergence to a consensus across individuals would occur from

round one to round two
- SIGs would not be as affected by social announcements as CSGs.

CSGs were found to be undervalued (relative to SIGs) in a single round setup. A two-round setup corrected this undervaluation. Specifically, it is more likely that the second round leads to a best possible prediction/decision/valuation than the first round (Chen et al., 2004; Grainger, 2017; Grainger et al., 2015). Therefore, CSGs are more likely undervalued in the first round than overvalued in the second round. This adds weight to similar previous comments made by researchers about the importance of deliberative processes for social choice (Himes and Muraca, 2018; Chan et al., 2018)).

The web-tool that we used here (which facilitates a deliberative process) could be adapted for use in innumerable other situations (three separate projects underway by authors include studies of the relative 'value' of: research projects; suicide prevention strategies; and environmental management activities). Perhaps more importantly, our insights open doors for other researchers to develop new (two-step) social learning applications. The takeaway of this study is that logically consistent social preferences are indeed possible when social learning occurs.

Statements

Competing interests statement

The authors whose names are listed above certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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I certify that no party having a direct interest in the results of the research supporting this article has or will confer a benefit on me or on any organization with which I am associated AND, if applicable, I certify that all financial and material support for this research and work are clearly identified in the title page of the manuscript.

Data statement

Due to the sensitive nature of the data collected in this study, workshop participants were assured raw data would remain confidential and would not be shared.

Ethics statement

This research was performed with ethics approval per James Cook University Ethics Number: (JCU) H6500.

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Appendix A. Supplementary data

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