CBESS Discussion Paper 17-01R

University of East Anglia

cbess
Centre for Behavioural and Experimental Social Science

Identifying discrete behavioural types: A re-analysis of public goods game contributions by Hierarchical clustering

by Francesco Fallucchi *
R. Andrew Luccasen, III**
Theodore L. Turocy***

*LISER
**Mississippi University for Women
***School of Economics and CBESS, University of East Anglia

Abstract
We propose a framework for identifying discrete behavioural types in experimental data.We re-analyse data from six previous studies of public goods voluntary contributions games. Using hierarchical clustering analysis, we construct a typology of behaviour based on a similarity measure between strategies. We identify four clearly distinct behavioural types, which together account for about 90% of participants. Compared to previous approaches, our method produces a classification in which different types are more clearly distinguished in terms of strategic behaviour and the resulting economic implications.

JEL classification codes
C65, C71, H41.

Keywords
behavioural types, cluster analysis, cooperation, public goods

Centre for Behavioural and Experimental Social Science
University of East Anglia
Norwich Research Park
Norwich NR4 7TJ
United Kingdom
www.uea.ac.uk/cbess

Identifying discrete behavioural types: A re-analysis of public goods game contributions by hierarchical clustering*

Francesco Fallucchi
LISER

R. Andrew Luccasen, III
Mississippi University for Women

Theodore L. Turocy
University of East Anglia

August 8, 2017

Abstract

We propose a framework for identifying discrete behavioural types in experimental data. We re-analyse data from six previous studies of public goods voluntary contributions games. Using hierarchical clustering analysis, we construct a typology of behaviour based on a similarity measure between strategies. We identify four clearly distinct behavioural types, which together account for about 90% of participants. Compared to previous approaches, our method produces a classification in which different types are more clearly distinguished in terms of strategic behaviour and the resulting economic implications.

Keywords: behavioural types, cluster analysis, cooperation, public goods

JEL Classifications: C65, C71, H41.

1 Introduction

The heterogeneity in decision-making behaviour observed in both field settings and their laboratory counterparts is by turns a great joy and a great frustration to practitioners of behavioural

*Fallucchi and Turocy acknowledge the support of the Network for Integrated Behavioural Science (Economic and Social Research Council Grant ES/K002201/1). We thank Daniele Nosenzo, Abhijit Ramalingam, and Marc Willinger, as well as seminar participants at Queen's University Belfast, University of East Anglia, and University of Nottingham for useful comments, as well as the authors of the cited previous studies for generously providing their data. All errors are the responsibility of the authors. Corresponding author: T.Turocy@uea.ac.uk.

economics. The richness in the variety of individual behaviour is evidence that people are indeed different, and approach the same economic decision-making task in a variety of ways. However, a parsimonious, practical, and tractable economic model should capture the commonalities in behaviour. Extracting those commonalities from the embarrassment of riches offered by the data is an important challenge in the development of behavioural economics and game theory.

One way forward is to posit a set of distinct behavioural types, which we refer to as a *typology*, in which the number of types is small. In this paper we will focus on the case of public goods voluntary contribution games (VCGs), for which Fischbacher et al. (2001) have proposed one such typology, which groups participants into four types. We choose this as an interesting setting because the *P-experiment* protocol introduced by Fischbacher et al., based on the linear VCG (Ledyard, 1997), has been employed as a standard methodology by many studies conducted in various languages and locations. (Kocher et al., 2008) We note that the idea of a discrete typology is not restricted to these games; for example, the successful level-k framework introduced by Stahl and Wilson (1995) likewise features a small number of types. The analysis we conduct in this paper benefits from being able to re-use data from a number of studies using a sufficiently similar protocol.

Not all heterogeneity seems to be summarised well by a discrete typology. For example, in Tullock contests the average bids of participants tend to spread out over an interval. (Chowdhury et al., 2014) For a discrete typology to be a fair representation of the data, it is desirable that the behaviour of two participants classified as different types should be sufficiently distinct, and that it should be clear where to draw the boundaries between different types.

We propose the use of hierarchical cluster analysis as a framework for determining whether it is possible to satisfy these desiderata, and further for guiding how many types to include in a typology. Using the data from six previous studies using the P-experiment protocol, we divide participants into five types. Each type exhibits a strategically distinct behavioural pattern, with implications for the performance of the voluntary contributions mechanism.

Two types in the typology of Fischbacher et al. map closely onto types in our typology. Both methods identify a type which contributes zero or a nominal amount to the public good in most contingencies; zero contribution is the dominant strategy that maximises a participant's own earnings. Another type, which we term *strong conditional cooperators*, is anchored around participants who match, on a one-for-one basis, the average contribution of the other participants in their group.

The main distinction between the typologies is that ours identifies a distinct mode of conditional cooperation, which we label *weak conditional cooperators*. These participants respond to higher contributions by others in their group by increasing their contributions, but at a rate less than one-for-one. We illustrate, using silhouette analysis (Rousseeuw, 1987), that drawing this distinction among conditional cooperators creates types which are much more cohesive. Participants classified as strong conditional cooperators also make generally higher unconditional contributions than those classified as weak conditional cooperators. This suggests that the underpinnings of the behaviour of weak conditional cooperators may be distinct from those of strong conditional cooperators. In letting the data speak for itself, unsupervised classification approaches can identify distinct modes of behaviour unanticipated a priori by either theorists or experimenters.

2 The game

The experiments used in our analysis involve one-shot interaction among participants in a VCG game. Participants are anonymously placed into groups with M members. Each participant receives G *tokens*. She can allocate any number of tokens between 0 and G to a group account; tokens not allocated to the group account are kept in her private account. We refer to the tokens allocated to the group account as her *contribution*. The participant receives a point for each token kept in her private account. Each token contributed to the group account yields $P > 1$ points, which are then split equally among the group members. The parameters P and M are chosen so that the marginal per-capita return (MPCR), P/M, is less than one. With these parameters, a participant who cares only about maximising her own earnings has a strictly dominant strategy, which is to contribute no tokens. In contrast, the strategy profile that maximises total earnings of the group is for each member to contribute all G tokens.

In the P-experiment protocol, contributions are made in two stages. In Stage 1, $M - 1$ of a group's members make their contributions. The remaining member of the group learns the average contribution of other group members, and then decides on her contribution. A participant does not know whether she will make her contribution in Stage 1 or Stage 2, nor, if she is to be the Stage 2 contributor, what the average contribution of the other members in Stage 1 will turn out to be. Decisions are therefore elicited using the *strategy method* (Selten, 1967). Each participant i states what her contribution will be if she is chosen to contribute in Stage 1; we write this unconditional contribution as u^i. She also states her contribution in Stage 2, for each possible realisation of the average contribution of the other members of her group.[1] We call these Stage 2 contributions the *contribution strategy*. We write the contribution strategy of a participant i as a vector c^i. The component c^i_g is the contribution of participant i in Stage 2, if the other group members contribute g tokens on average in Stage 1. The contribution strategy is the basis for identifying behavioural types.

[1] In the P-experiment protocol, the average contribution of other group members is rounded to the nearest integer.

3 Typologies

Let $\mathcal{N}$ denote the set of participants, and $\mathcal{C} = \{(i, c^i)\}_{i\in\mathcal{N}}$ be the set of all participants paired with their contribution strategies.[2] We define a *typology* T as a partition of $\mathcal{C}$ into equivalence classes. Each equivalence class is interpreted as a distinct behavioural type. We write $T(i)$ as the type of participant i in typology T.

We propose a satisfactory typology should satisfy three (heuristic) criteria:

1. If two participants i and j are classified as the same type, $T(i) = T(j)$, then their behaviour should be "similar."

2. If two participants are deemed different types, $T(i) \neq T(j)$, then their behaviour should be sufficiently "dissimilar."

3. A typology should be useful in organising choices not used in the classification process. In the case of the P-experiment protocol, the Stage 1 unconditional choices u^i are not used in the classification; if the Stage 2 choices are capturing qualitative differences in how participants approach the VCG, we would expect that Stage 1 choices will vary across at least some of the types.

The existing state-of-the-art in the literature is the typology based on Fischbacher et al. (2001), which we will call T^F. T^F partitions participants into one of four types. These types are defined by rules which combine stereotypical behaviour and rules of thumb. As set by Fischbacher et al. these are

- *Free-riders* (FR) always maximise individual earnings by keeping all tokens in the private account, irrespective of the outcome of the first stage.

- *Conditional cooperators* (CC) increase their contributions to the group account based on higher contributions by others in the first stage. A participant i is deemed a conditional cooperator by testing whether the Spearman's ρ correlation coefficient between the vector $[0, 1, \ldots, G]$ of possible average contributions g and the participant's strategy $[c^i_0, c^i_1, \ldots, c^i_G]$ is significantly positive at significance level ≤ 0.001.

- *Hump-shaped* (HS) contributors are identified based on visual classification of contribution strategies, in which c^i_0 and c^i_G are small, but c^i_g is larger for some intermediate values $0 < g < G$; these strategies often have a triangular shape when plotted.

[2] We define $\mathcal{C}$ in this way as the analysis will make use of the number of participants who choose the same contribution strategy.

- *Others* (OT) is the residual type, comprised of participants whose whose contribution strategies do not satisfy the criteria defining the other types.

Other studies have used modifications to these criteria. Fischbacher et al. (2012) define conditional cooperators as participants with a monotonic contribution pattern with at least one increase. Rustagi et al. (2010) split conditional cooperators based on the level of statistical significance of the correlation between own contributions and the contributions of other group members, in which strong conditional cooperators are those for whom Spearman's ρ is positive at significance level ≤ 0.001 and weak conditional cooperators are those for whom it is positive at significance level in $(0.001, 0.05]$. They classify a participant as a free-rider if at most one entry in the contribution strategy c^i is positive. By adjusting the classification criteria, one can make the residual "other" group smaller, but with the possibility that a participant's contribution strategy might satisfy the criteria for more than one other type.

We construct a typology T^H based on hierarchical cluster analysis. We operationalise the notion of (dis-)similarity between the contribution strategies c^i of a participant i and c^j of a participant j as the Manhattan distance between the vectors, $d(c^i, c^j) = \sum_{g=0}^{G} \left|c_g^i - c_g^j\right|$. The distance between c^i and c^j is the expected difference between the Stage 2 contributions of participants i and j, if the average contribution g of other group members is chosen uniformly at random. Two contribution strategies separated by a smaller distance are considered more similar.

We use Ward's minimum variance method (Ward, 1963) to cluster subjects based on this distance measure.[3] This method does not pre-specify the number of clusters generated. For any $C = 1, 2, \ldots, |\mathcal{C}|$, Ward's method generates a typology $\tilde{T}^H(C)$ which partitions $\mathcal{C}$ into exactly C groups. The partition $\tilde{T}^H(C)$ is one that minimises the within-group variance among all possible partitions with exactly C groups. Operationally, these partitions are constructed recursively. The partition $\tilde{T}^H(C-1)$ is generated from $\tilde{T}^H(C)$ by combining together the two "most similar" elements of $\tilde{T}^H(C)$. This process corresponds with the first criterion, that participants who are classified as being of the same type should have similar behaviour.

To select the typology T^H from among the candidates $\{\tilde{T}^H(C)\}_{C=1}^{|\mathcal{C}|}$, we use the Je(2)/Je(1) index. (Duda and Hart, 1973) Briefly, this index trades off (dis-)similarity within clusters and (dis-)similarity across clusters. This corresponds with the second criterion, as minimisation of this measure indicates more distinct clustering, that is, that participants who are classified as being of different types should have dissimilar behaviour.

Given a typology T, silhouette analysis (Rousseeuw, 1987) is a way of comparing within-type similarity and across-type dissimilarity. For any participant i, the average distance from participant

[3] As an additional robustness check, we conducted clustering using k-means, which we report on in Appendix A. The resulting clusters are very similar to those obtained using Ward's method.

i's contribution strategy to the contribution strategies of other participants of a given type $t \in T$ is

$$a(i,t) = \frac{\sum_{j \neq i: T(j)=t} d(c^i, c^j)}{\sum_{j \neq i: T(j)=t} 1}.$$

For participant i, the distance to the "closest" type which is different from the type to which i is assigned is

$$b(i) = \min_{t \neq T(i)} a(i,t).$$

The participant's silhouette index is then defined as

$$s(i) = \frac{b(i) - a(i, T(i))}{\max\{b(i), a(i, T(i))\}}.$$

The silhouette index ranges from -1 to +1. Values greater than zero indicate that the members of i's type are closer, on average, than the members of the next closest type.

4 Results

We re-analyse the data from six VCG experiments using the P-experiment protocol, published between 2001 and 2016. We surveyed the literature for studies which met these criteria:

- P-experiment protocol already published in a peer-reviewed journal as of September 2016;
- Participants played the VCG game in groups of 4;
- Participants were endowed with 20 tokens;
- Marginal per capita return of the public good (MPCR) equal to 0.4 points per token.

We identified a total of 9 studies satisfying these criteria. We contacted the authors of these studies and were able to obtain data for 6 of the papers.[4] The experiments for which we obtained data were conducted in four different countries and four different languages, with a total of $N = 551$ participants.[5]

[Table 1 about here.]

[4]In the case of the other 3 papers, we either received no response, or the authors were not able to find the data.

[5]In Appendix B we compare the two typologies with three VCG experiments (Kocher et al., 2008; Frackenpohl et al., 2015; Burton-Chellew et al., 2016) which used different parameters or variations on the P-experiment protocol. The results produced by cluster analysis using those data are broadly consistent with the results we report here.

The classification proportions identified for each study, and for the population as a whole, are given in Table 1a for typology T^F and Table 1b for typology T^H.[6] The clusters in T^H are derived endogenously from the data, and so for expositional purposes we attach to each a label, based on ex-post inspection, which captures the modal or stereotypical behaviour observed in the cluster. The inspirations for these type labels are heatmaps of contribution strategies assigned to each type, as shown in Figure 1a for T^F and Figure 1b for T^H. The heatmap for a type t is produced from the contribution strategies of all participants assigned to a type, by constructing the set $\{(k, c_k^i)\}_{T(i)=t,k=0,\ldots,20}$. The frequencies of the ordered pairs in this set are used to generate the heatmap, with darker shades corresponding to higher frequencies. In all figures, unfilled diamonds indicate the average contribution of the type, conditional on the first stage outcome.

[Figure 1 about here.]

We now introduce the types produced in T^H via hierarchical clustering. *Own-maximisers* (OWN, 25.8% of participants), named because the modal allocation is zero, contribute very little to the group account in all contingencies. The modal behaviour among *strong conditional cooperators* (SCC, 38.8%) is to match average contributions token-for-token. The typology distinguishes SCC from *weak conditional cooperators* (WCC, 18.9%), who have contribution strategies that increase in the contributions of other group members on average about half as much as the other group members. There is a small, distinct group of *unconditional cooperators* (UNC, 4.7%), corresponding to contributions which are at or near full contribution to the group account. This labeling parallels that of Kurzban and Houser (2005), where, in a repeated game, those whose always contribute more than the average of the others in their group are called (unconditional) "cooperators". The final cluster (11.8%) is labeled *various* (VAR), and contribute on average about one-half of the tokens. This group is the most diverse; in addition to a high frequency of contributions exactly equal to 10, there are also "negative conditional contributors" (Herrmann and Thöni, 2009) who decrease their contribution in response to higher contributions by others.

[Table 2 about here.]

The relationship between the typologies T^F and T^H can be seen in Table 2. Each cell contains the number of participants who are classified under T^F into the column label type, and under T^H into the row label type. Conditional cooperators in T^F split primarily between strong and weak conditional cooperators in T^H, while hump-shaped contributors are distributed across both conditional cooperator types and own-maximisers in T^H. These observations combined with the heatmaps suggest that conditional cooperators and hump-shaped contributors under T^F are not particularly cohesive types, in that they group dissimilar behaviours within the same "type".

[6]The typology T^F is generated by the procedure proposed in Fischbacher et al. (2001) as given above, and therefore differs slightly from the percentages quoted in the corresponding papers where the authors used a variant approach.

[Figure 2 about here.]

We evaluate the cohesion of the types generated by T^H compared to T^F using silhouette plots (Rousseeuw, 1987) in Figure 2. The silhouette of a type t is generated by sorting members of t in decreasing order by their silhouette index $s(i)$, and plotting those sorted $s(i)$ values against the participant's sorted rank. In the T^F typology, a majority of participants identified as hump-shaped contributors (29 of 49) have strategies which are on average closer to one of the other three types' strategies, than to other hump-shaped contributors. Among those identified as others, 93 of 107 have strategies closer on average to one of the other three types than to the rest of those considered others. Many conditional cooperators likewise have negative indices.

We compare this with the silhouette plot for the types generated by typology T^H. Unconditional cooperators are identified as a distinct and coherent type, with members having large positive indices. Own-maximisers all have positive indices, while almost all strong conditional cooperators (197 of 214) do as well. The distinction between strong conditional cooperators and weak conditional cooperators helps to avoid the large negative indices observed among T^F's conditional cooperators. The heterogeneity of the remaining participants classified as various is evident in the range of indices among the participants; although a majority (39 of 65) have negative indices, the magnitudes are much smaller than those measured for the others type in T^F. Overall, 65.7% of the participants have a higher index in T^H than T^F. The average index increases from 0.19 in T^F to 0.42 in T^H, and the median from 0.27 to 0.46. The medians are significantly different ($p < 0.001$ using sign-rank test).

The 5 types in T^H is the number recommended by the Duda-Hart Je(2)/Je(1) rule. As rules for determining the number of clusters are heuristic, others are proposed in the literature. For example, the rule of Caliński and Harabasz (1974) produces only 4 clusters. The alternate four-cluster typology $\tilde{T}^H(4)$ differs from T^H in that it combines the clusters we label as unconditional cooperators and various. Using $\tilde{T}^H(4)$ does not change significantly the conclusions outlined above. Common practice (Everitt et al., 2010) suggests that when different rules suggest different numbers of clusters, it is conservative to use the larger number of clusters.[7] We additionally note that the silhouette plot indicates that the unconditional cooperators represents a coherent and distinct behavioural pattern, as almost all participants classified in that type have a positive silhouette index.

[Figure 3 about here.]

Our third criterion for constructing typologies is that a typology ideally should correlate with some data not used in its construction. In the P-experiment protocol, we also have the Stage 1

[7] No standard rule suggests 6 clusters. $\tilde{T}^H(6)$ differs from T^H by splitting weak conditional cooperators into two categories.

unconditional contributions u^i for each participant i, which are not used in constructing T^F or T^H. There is no previous evidence that the T^F typology is useful in explaining variations in Stage 1 contributions. Excluding free-riders, the types in T^F are defined on patterns of contributions, rather than absolute levels. In contrast, types in T^H are permitted to depend on both patterns and absolute levels of contributions.

Different types in T^H generate distinct patterns of Stage 1 contributions. Figure 3 shows the distributions of Stage 1 contributions, grouped by type assignment based on Stage 2 contribution strategies. In the T^F typology, free-riders allocate on average 2.15 tokens (with a mode at zero), while the other three types have dispersed distributions of Stage 1 contributions with means and medians near half of the endowment of 20 tokens. The Stage 1 contribution of free-riders is different from other types (all Bonferroni multiple-comparisons tests $p < 0.001$), while there is no significant difference in Stage 1 allocations among the remaining types.

Using the T^H typology, the ranking and magnitude of average allocations is consistent with the classification based on Stage 2 strategies. Own-maximisers contribute the least (3.20 tokens), followed by weak conditional cooperators (8.23), strong conditional cooperators (10.04), various (11.42) and unconditional cooperators (13.96). Stage 1 contributions are significantly different across the five types. The mean allocation of own-maximisers is significantly lower than all other clusters (one-way analysis of variance with multiple comparisons and Bonferroni correction, all $p \leq 0.001$). There is a significant difference in contributions between weak conditional cooperators and strong conditional cooperators ($p = 0.088$), but no significant differences between the strong conditional cooperators and various, nor between the various and unconditional cooperators (all other comparisons $p < 0.011$).

5 Summary

We propose hierarchical cluster analysis as a useful tool for identifying whether a model with a discrete number of behavioural types is an appropriate description of experimental data. In VCGs using the P-experiment protocol, we confirm that own-maximisers and strong conditional cooperators (matching the contributions of others one-to-one) emerge as the cores of clearly-distinguished behavioural groups. In part because cluster analysis considers both within-group similarity as well as across-group dissimilarity, weak conditional cooperation also emerges as a distinct mode of behaviour. This provides an independent justification for a similar distinction among types of conditional cooperator which has been proposed in several previous studies, including Chaudhuri and Paichayontvijit (2006), Rustagi et al. (2010), Gächter et al. (2012) and Cheung (2014).

With the addition of the small group of unconditional cooperators, these four types comprise approximately 88% of all participants across the six studies; excluding Herrmann and Thöni (2009) this figure rises to 95%. Notwithstanding the noise inherent in choice data, most participants' behaviour is reasonably well-approximated by one of four stereotypical patterns of behaviour.

Although increasingly popular in analyses of "big" datasets, cluster analysis and similar techniques are at present rarely used with experimental data. Rong and Houser (2015b) use k-means clustering to explore the dataset from Rong and Houser (2015a), in which participants make investment decisions in a network context. Because of the network, investment decisions have spillovers, their game also has a public-goods nature. They find three distinct types, and show that the proportions of those three types shift across treatments. The cluster analysis therefore provides lower-level evidence to underpin the treatment-level effects reported in the original paper.

Interesting experimental designs often generate unanticipated results, which call for the development of improved or new models. Unsupervised classification methods such as clustering are one option for a structured approach to informing that process. In the case of this paper, cluster analysis confirms the organisation of the rich, 21-dimensional decisions of the contribution strategy into a small number of behaviourally-distinct types, suggesting a small typology provides a parsimonious but faithful summary of behaviour.

References

Maxwell N. Burton-Chellew, Claire El Mouden, and Stuart A. West. Conditional cooperation and confusion in public-goods experiments. *Proceedings of the National Academy of Sciences*, 113(5):1291–1296, 2016.

Tadeusz Caliński and Jerzy Harabasz. A dendrite method for cluster analysis. *Communications in Statistics: Theory and Methods*, 3(1):1–27, 1974.

Edward J. Cartwright and Denise Lovett. Conditional cooperation and the marginal per capita return in public good games. *Games*, 5(4):234–256, 2014.

Ananish Chaudhuri and Tirnud Paichayontvijit. Conditional cooperation and voluntary contributions to a public good. *Economics Bulletin*, 3(8):1–14, 2006.

Stephen L. Cheung. New insights into conditional cooperation and punishment from a strategy method experiment. *Experimental Economics*, 17(1):129–153, 2014.

Subhasish M. Chowdhury, Roman M. Sheremeta, and Theodore L. Turocy. Overbidding and overspreading in rent-seeking experiments: Cost structure and prize allocation rules. *Games and Economic Behavior*, 87:224–238, 2014.

Richard O. Duda and Peter E. Hart. *Pattern Classification and Scene Analysis*, volume 3. John Wiley & Sons, New York, 1973.

Brian S. Everitt, Sabine Landau, Morven Leese, and Daniel Stahl. Some final comments and guidelines. *Cluster Analysis, 5th Edition*, pages 257–287, 2010.

Urs Fischbacher and Simon Gächter. Social preferences, beliefs, and the dynamics of free riding in public goods experiments. *American Economic Review*, 100(1):541–556, 2010.

Urs Fischbacher, Simon Gächter, and Ernst Fehr. Are people conditionally cooperative? Evidence from a public goods experiment. *Economics Letters*, 71(3):397–404, 2001.

Urs Fischbacher, Simon Gächter, and Simone Quercia. The behavioral validity of the strategy method in public good experiments. *Journal of Economic Psychology*, 33(4):897–913, 2012.

Gerrit Frackenpohl, Adrian Hillenbrand, and Sebastian Kube. Leadership effectiveness and institutional frames. *Experimental Economics*, pages 1–22, 2015.

Simon Gächter, Daniele Nosenzo, Elke Renner, and Martin Sefton. Who makes a good leader? Cooperativeness, optimism, and leading-by-example. *Economic Inquiry*, 50(4):953–967, 2012.

Benedikt Herrmann and Christian Thöni. Measuring conditional cooperation: A replication study in Russia. *Experimental Economics*, 12(1):87–92, 2009.

Martin G. Kocher, Todd Cherry, Stephan Kroll, Robert J. Netzer, and Matthias Sutter. Conditional cooperation on three continents. *Economics Letters*, 101(3):175–178, 2008.

Robert Kurzban and Daniel Houser. Experiments investigating cooperative types in humans: A complement to evolutionary theory and simulations. *Proceedings of the National Academy of Sciences*, 102(5):1803–1807, 2005.

John Ledyard. Public goods: A survey of experimental research. In John H. Kagel and Alvin E. Roth, editors, *Handbook of Experimental Economics*. Princeton University Press, Princeton NJ, 1997.

Raphaële Préget, Phu Nguyen-Van, and Marc Willinger. Who are the voluntary leaders? Experimental evidence from a sequential contribution game. *Theory and Decision*, pages 1–19, 2016.

Rong Rong and Daniel Houser. Growing stars: A laboratory analysis of network formation. *Journal of Economic Behavior & Organization*, 117:380–394, 2015a.

Rong Rong and Daniel Houser. Exploring network behavior using cluster analysis. In *New Perspectives on Internationalization and Competitiveness*, pages 161–182. Springer, 2015b.

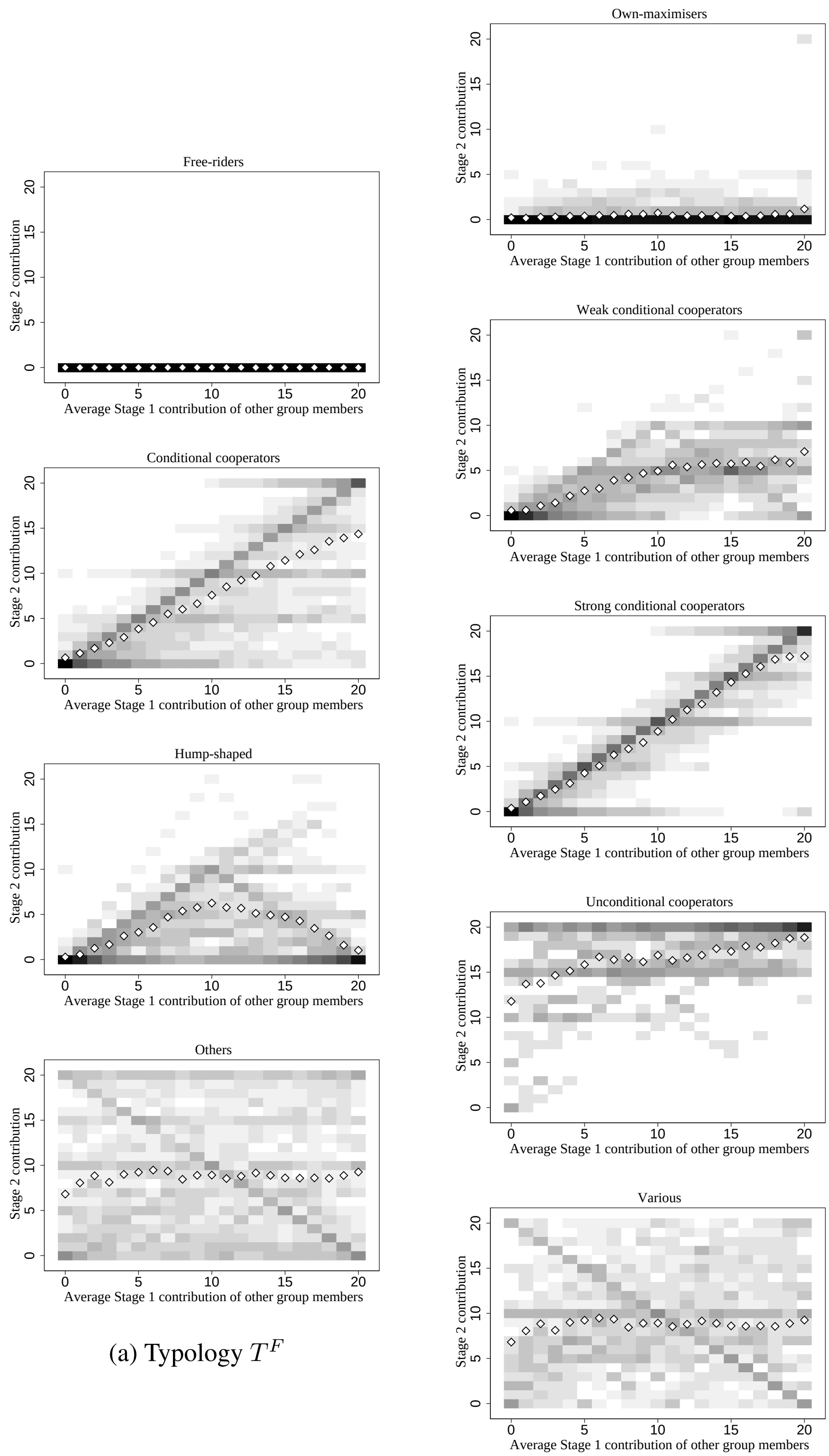
Peter J. Rousseeuw. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20:53–65, 1987.

Devesh Rustagi, Stefanie Engel, and Michael Kosfeld. Conditional cooperation and costly monitoring explain success in forest commons management. *Science*, 330(6006):961–965, 2010.

Reinhard Selten. Die strategiemethode zur erforschung des eingeschränkt rationalen verhaltens im rahmen eines oligopolexperiments. In H. Sauerman, editor, *Beiträge zur Experimentellen Wirtschaftsforschung*. JCB Mohr, Tübingen, 1967.

Dale O. Stahl and Paul W. Wilson. On players' models of other players: Theory and experimental evidence. *Games and Economic Behavior*, 10(1):218–254, 1995.

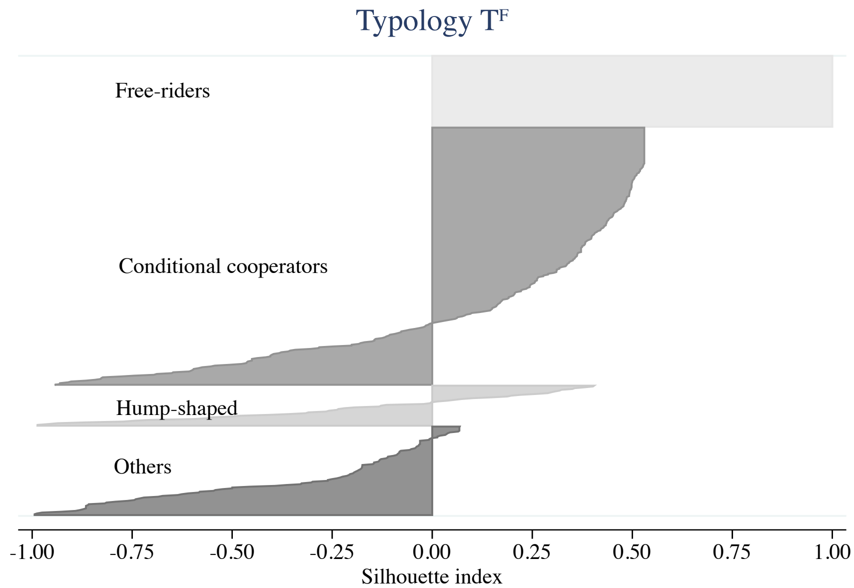
Joe H. Ward. Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association*, 58(301):236–244, 1963.



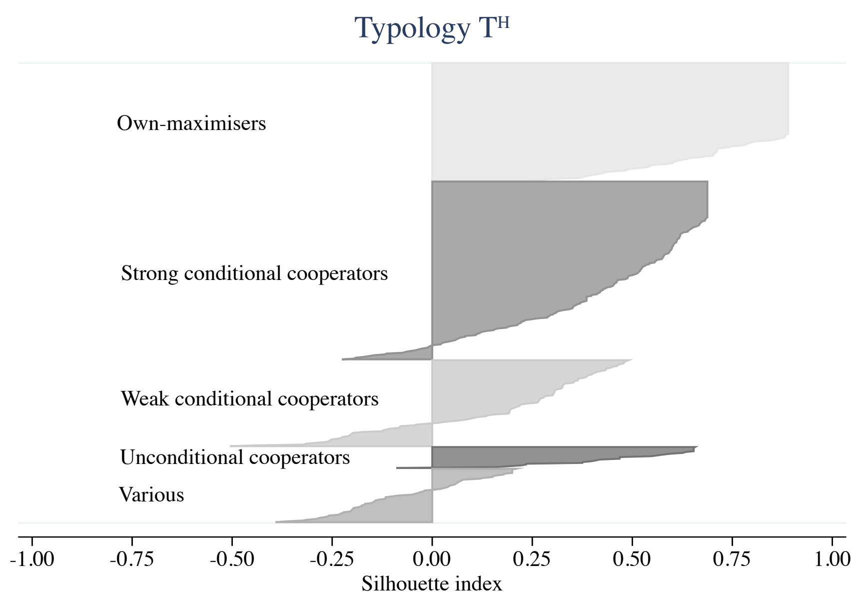
(a) Typology T^F

(b) Typology T^H

Figure 1: Heatmaps of contribution strategies of the participants classified in each type. The heatmap for a type is produced from the contribution strategies of all participants classified as that type. Contribution levels that appear more frequently in the contribution strategies for a given Stage 1 outcome appear in darker shades. The unfilled diamonds indicate the average contribution of the type, conditional on the Stage 1 outcome.

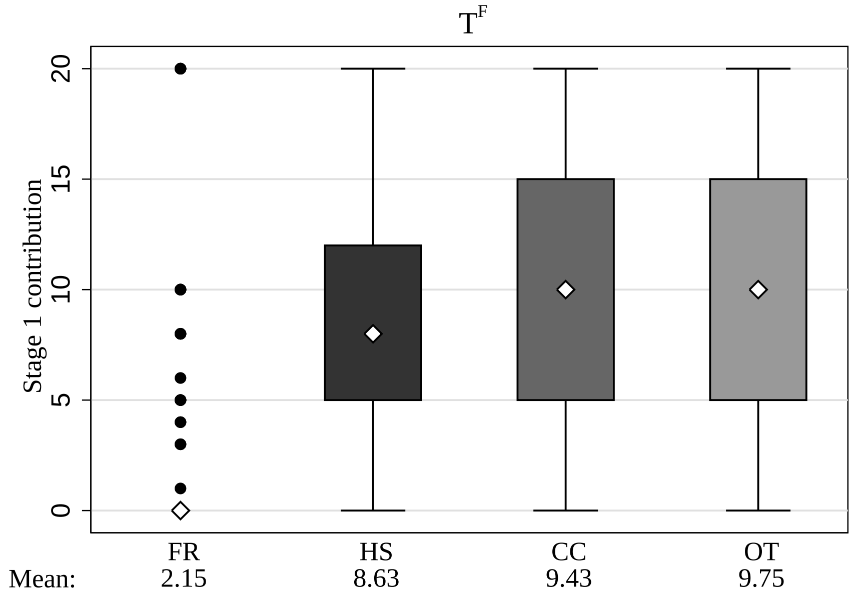


(a) Typology T^F

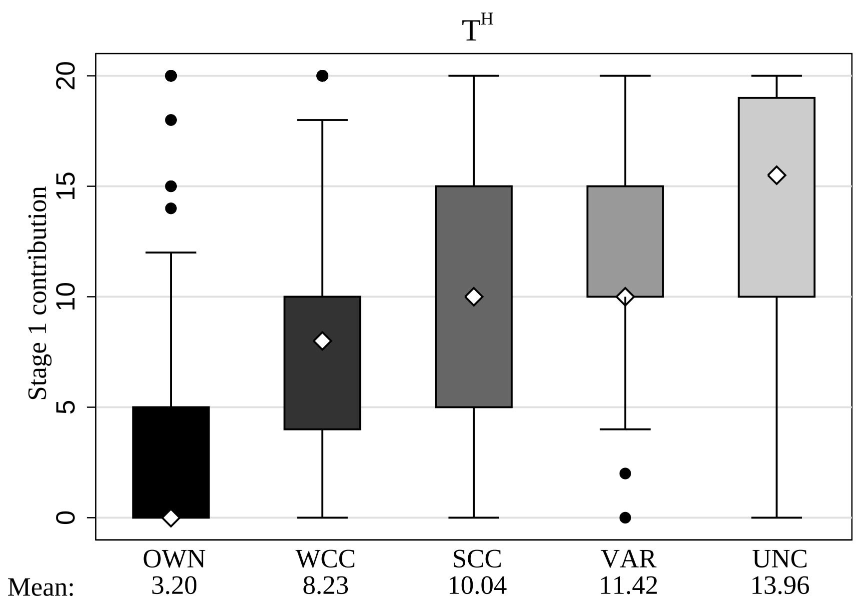


(b) Typology T^H

Figure 2: Silhouette plots of type clusters. Each participant is assigned an index in $[-1, 1]$, comparing the average distance between the participant's strategy and the strategies of participants of the same type, against the average distance to participants' strategies who are classified in the next closest type. A negative value indicates there is another type whose strategies are on average closer to the participant's strategy, than the strategies of other participants classified as the same type.



(a) Typology T^F



(b) Typology T^H

Figure 3: Boxplots of Stage 1 contributions by type, for each typology. Boxes indicate the interquartile range of the distribution; unfilled diamonds indicate medians. The whiskers indicate Tukey's adjacent values: the upper adjacent value is the upper quartile plus 1.5 times the interquartile range; the lower adjacent value is the lower quartile minus 1.5 times the interquartile range. Black dots indicate outliers, values which fall outside the whiskers.

Study	Country	FR	CC	HS	OT	N
Fischbacher et al. (2001)	SUI	29.6%	50.0%	13.6%	6.8%	44
Herrmann and Thöni (2009)	RUS	6.3%	52.5%	6.2%	35.0%	160
Fischbacher and Gächter (2010)	SUI	22.9%	50.7%	12.1%	14.3%	140
Fischbacher et al. (2012)	GBR	14.7%	69.1%	6.6%	9.6%	136
Cartwright and Lovett (2014)	GBR	6.5%	74.2%	3.2%	16.1%	31
Préget et al. (2016)	FRA	22.5%	37.5%	15.0%	25.0%	40
Overall		**15.6%**	**56.1%**	**8.9%**	**19.4%**	**551**

(a) Typology T^F. FR: free-riders. CC: conditional cooperators. HS: hump-shaped. OT: others.

Study	Country	OWN	SCC	WCC	UNC	VAR	N
Fischbacher et al. (2001)	SUI	38.6%	29.5%	18.2%	2.3%	11.4%	44
Herrmann and Thöni (2009)	RUS	10.6%	36.3%	19.4%	5.6%	28.1%	160
Fischbacher and Gächter (2010)	SUI	39.3%	36.4%	17.1%	3.6%	3.6%	140
Fischbacher et al. (2012)	GBR	27.2%	50.5%	18.4%	3.7%	0.7%	136
Cartwright and Lovett (2014)	GBR	13.0%	45.2%	29.0%	3.2%	9.7%	31
Préget et al. (2016)	FRA	30.0%	25.0%	17.5%	12.5%	15.0%	40
Overall		**25.8%**	**38.8%**	**18.9%**	**4.7%**	**11.8%**	**551**

(b) Typology T^H. OWN: own-maximisers. SCC: strong conditional cooperators. WCC: weak conditional cooperators. UNC: unconditional cooperators. VAR: various.

Table 1: Distributions of types as identified by typologies T^F and T^H. N is total number of participants in each study.

		T^F				
		FR	CC	HS	OT	Total
T^H	OWN	86	24	19	13	**142**
	SCC	0	206	7	1	**214**
	WCC	0	70	21	13	**104**
	UNC	0	10	0	16	**26**
	VAR	0	15	2	48	**65**
	Total	**86**	**325**	**49**	**91**	**551**

Table 2: Comparison of the T^F and T^H typologies. Each row corresponds to one type in the T^H typology, and each column to one type in the T^F typology. The cells report the number of participants overall to be classified in the row type in T^H and the column type in T^F.

A Comparison of clustering methods

As a robustness check, we conduct the clustering using k-means instead of Ward's linkage. Figure 4 displays the heatmaps of the clusters, with the clusters arising from Ward's linkage on the left and k-means on the right. The two methods generate very similar clusters; we therefore identify the k-means clusters using the same labels as for the Ward's linkage clusters.

[Figure 4 about here.]

[Table 3 about here.]

[Table 4 about here.]

Table 3 compares the classifications using the two approaches. The entries on the diagonal count the number of participants classified in the "same" cluster by both approaches. The main difference is in drawing the boundary around the weak conditional cooperators: there is a group of participants labeled WCC by Ward's linkage who are considered OWN by k-means, and another group labeled SCC by Ward's linkage but WCC by k-means. Table 4 provides the percentages of types from each study as classified by k-means, which overall generates a somewhat larger group of own-maximisers relative to Ward's linkage.

B Other studies

Table 5 shows the results from the T^F and T^H typology from three other studies that differ in some of the criteria from the studies selected for the main analysis:

- In Kocher et al. (2008) participants play the VCG in groups of three rather than four.
- In Frackenpohl et al. (2015) the contribution in the second stage is conditional only on the contribution of one other group member, instead of the average of other group members.
- In Burton-Chellew et al. (2016) participants play in a group with three computer players.

We conduct separate cluster analyses for each of the studies. In all three cases the Je(2)/Je(1) rule recommends four clusters.

[Table 5 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

[Figure 7 about here.]

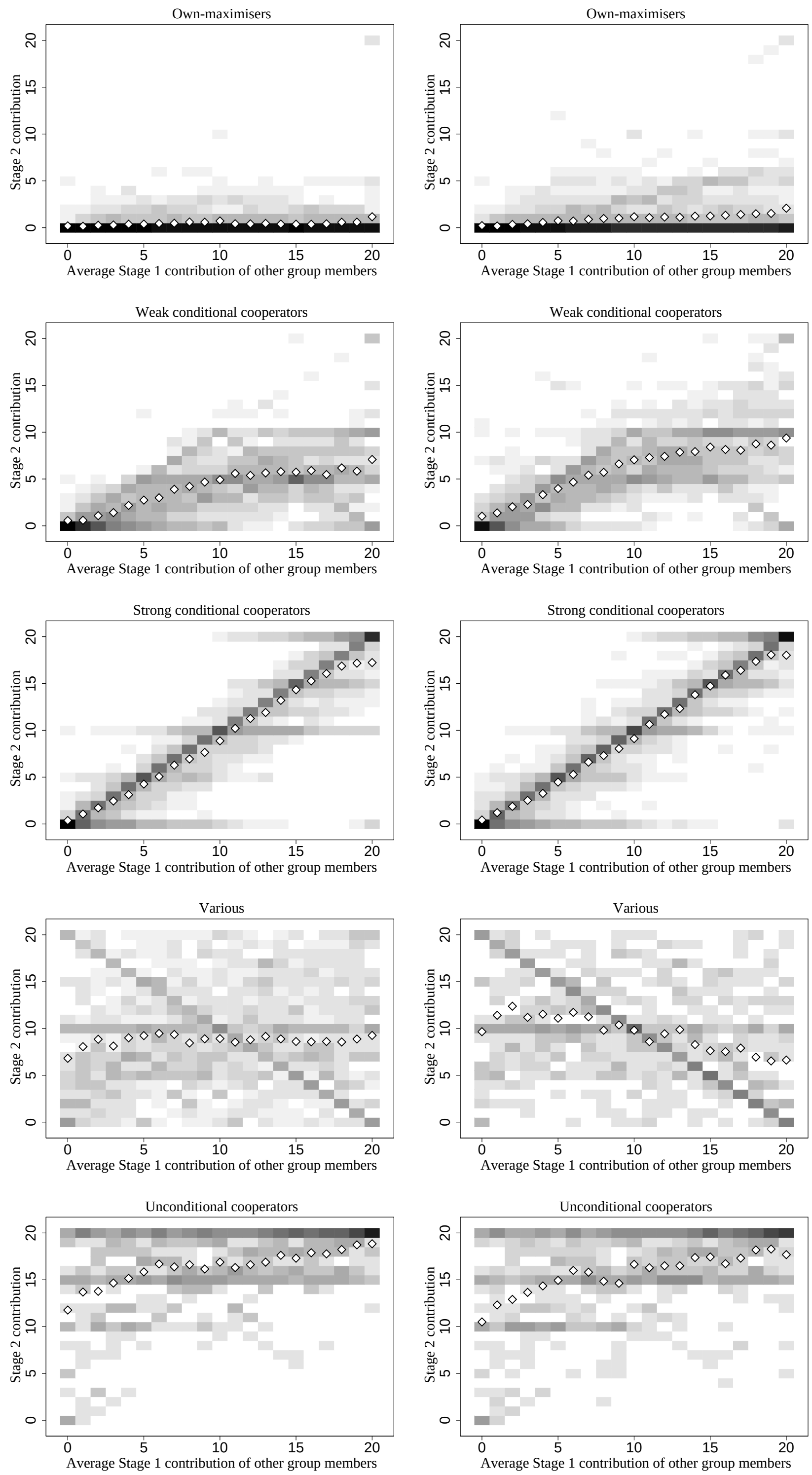
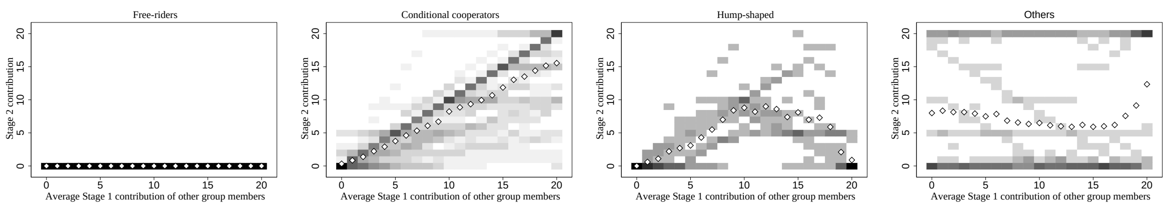
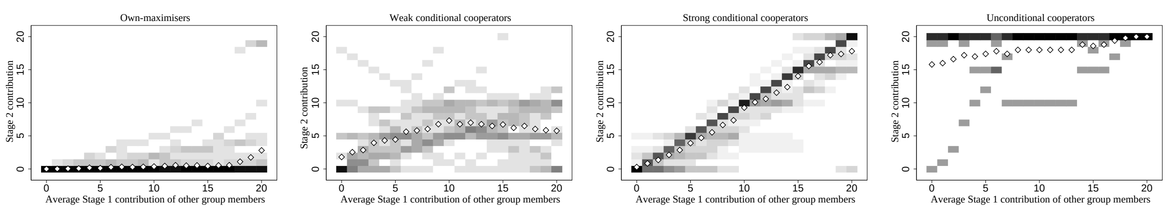


Figure 4: Clusters generated by Ward's linkage (left panels) and k-means (right panels).

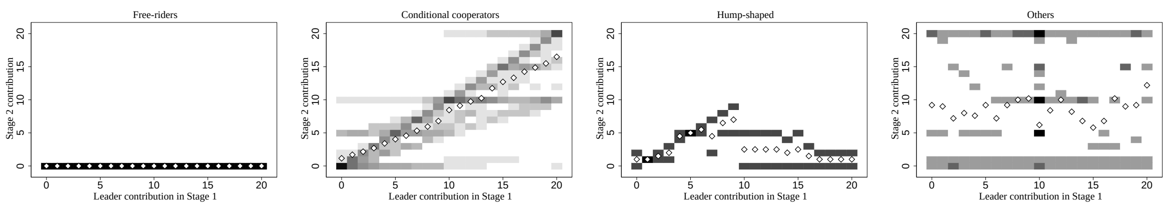


(a) T^F typology

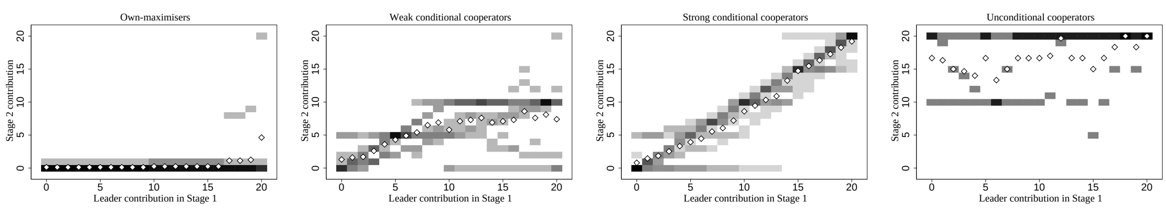


(b) T^H typology

Figure 5: Heatmaps of contribution strategies for Kocher et al. (2008).

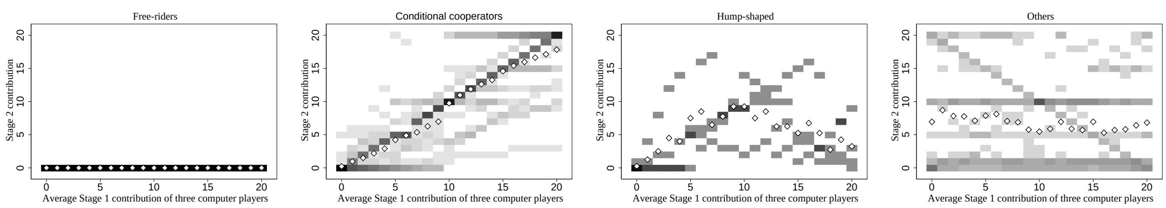


(a) T^F typology

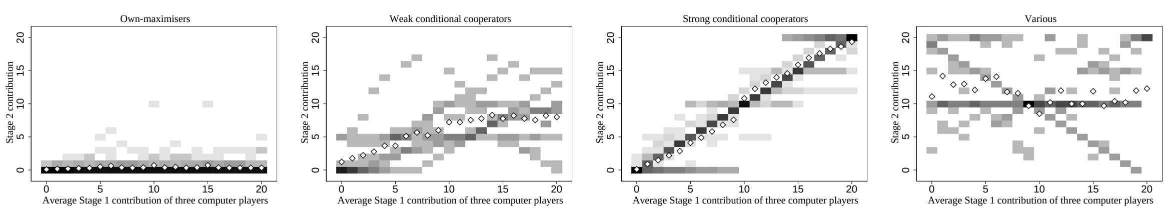


(b) T^H typology

Figure 6: Heatmaps of contribution strategies for Frackenpohl et al. (2015).



(a) T^F typology



(b) T^H typology

Figure 7: Heatmaps of contribution strategies for Burton-Chellew et al. (2016).

		k-means					
		OWN	WCC	SCC	UNC	VAR	Total
T^H	OWN	142	0	0	0	0	**142**
	WCC	41	62	1	0	0	**104**
	SCC	1	31	180	2	0	**214**
	UNC	0	0	0	26	0	**26**
	VAR	0	19	10	4	32	**65**
	Total	**184**	**112**	**191**	**32**	**32**	**551**

Table 3: Comparison of the T^H and k-means typologies. Each row corresponds to one type in the T^H typology, and each column to one type in the k-means typology. The cells report the number of participants overall to be classified in the row type in T^H and the column type in k-means.

Study	Country	OWN	SCC	WCC	UNC	VAR	N
Fischbacher et al. (2001)	SUI	47.7%	29.6%	15.9%	2.3%	4.5%	44
Herrmann and Thöni (2009)	RUS	18.8%	36.2%	23.1%	7.5%	14.4%	160
Fischbacher and Gächter (2010)	SUI	43.6%	33.6%	18.6%	3.5%	0.7%	140
Fischbacher et al. (2012)	GBR	36.8%	39.0%	18.4%	5.1%	0.7%	136
Cartwright and Lovett (2014)	GBR	19.4%	38.7%	32.3%	3.2%	6.4%	31
Préget et al. (2016)	FRA	40.0%	20.0%	17.5%	15.0%	7.5%	40
	Overall	**33.4%**	**34.7%**	**20.3%**	**5.8%**	**5.8%**	**551**

Table 4: Percentages of participants classified into each of the five types with k-means clustering. OWN are own-maximisers, SCC are strong conditional cooperators, WCC are weak conditional cooperators, UNC are unconditional cooperators, and VAR are various. N reports the total number of participants in each study.

Study	FR	CC	HS	OT	Total
Kocher et al. (2008)	24 (22.2%)	60 (55.6%)	10 (9.2%)	14 (13.0%)	108
Frackenpohl et al. (2015)	5 (13.9%)	24 (66.7%)	2 (5.5%)	5 (13.9%)	36
Burton-Chellew et al. (2016)	15 (20.8%)	36 (50.0%)	4 (5.6%)	17 (23.6%)	72

(a) T^F typology

Study	OWN	WCC	SCC	UNC	VAR	Total
Kocher et al. (2008)	37 (34.3%)	22 (20.4%)	44 (40.7%)	5 (4.6%)	- -	108
Frackenpohl et al. (2015)	8 (22.2%)	10 (27.8%)	15 (41.7%)	3 (8.3%)	- -	36
Burton-Chellew et al. (2016)	24 (33.3%)	9 (12.5%)	29 (40.3%)	- -	10 (13.9%)	72

(b) T^H typology

Table 5: Classification of participants (percentages in parentheses)