The Potential of Social Identity for Equilibrium Selection*

Roy Chen Yan Chen

September 11, 2009

Abstract

When does a common group identity improve efficiency in coordination games? To answer this question, we propose a group-contingent social preference model and derive conditions under which social identity changes equilibrium selection by changing the potential function. We test our predictions in the minimum effort game in the laboratory under parameter configurations which lead to an inefficient low-effort equilibrium for subjects with no group identity. Conversely, for those with a salient group identity, consistent with our theory, we find that learning leads to in-group coordination to the efficient high-effort equilibrium. Additionally, our theoretical framework reconciles empirical findings from a number of coordination game experiments.

Keywords: social identity, equilibrium selection, potential games, experiment
JEL Classification: C7, C91

*We would like to thank Tilman Borgers, Colin Camerer, David Cooper, Dan Friedman, Jacob Goeree, Benedikt Hermann, Nancy Kotzian, Sherry Xin Li, Yusufcan Masatlioglu, Rosemarie Nagel, Roberto Weber, and seminar participants at the University of Michigan and the 2008 International Meetings of the Economic Science Association (Pasadena, CA) for helpful discussions and comments, and Ashlee Stratakis for excellent research assistance. The financial support from the National Science Foundation through grants no. IIS-0325837 and SES-0720943 is gratefully acknowledged. Roy Chen: Department of Economics, University of Michigan, 611 Tappan Street, Ann Arbor, Michigan 48109-1220. Email: roywchen@umich.edu. Yan Chen: School of Information, University of Michigan, 1075 Beal Avenue, Ann Arbor, MI 48109-2112. Email: yanchen@umich.edu.

1 Introduction

Today's workplace is comprised of increasingly diverse social categories, including various racial, ethnic, religious and linguistic groups. Within this environment, many organizations face competition among employees in different departments, as well as conflicts between permanent employees and contingent workers (temporary, part-time, seasonal and contracted employees). While a diverse workforce contains a variety of abilities, experiences and cultures which can lead to innovation and creativity, diversity may also be costly and counterproductive if members of work teams find it difficult to integrate their diverse backgrounds and work together (Alesina and Ferrara 2005). This issue of integrating and motivating a diverse workforce is thus an important consideration for organizations. One method to achieve such integration is to develop a common identity. In practice, common identities have often been used to create common goals and values. For example, Nike founder Phil Knight and many of his employees have tattoos of the Nike "swoosh" logo on their left calves as a sign of group membership (Camerer and Malmendier 2007). To create a common identity and to teach individuals to work together towards a common purpose, companies have attempted various creative team-building exercises, such as simulated space missions where the crew works together to overcome malfunctions, perform research and keep life support systems operational while navigating through space (Ball 1999), and rowing competitions where "each person in the boat is totally reliant on other team members and therefore must learn to trust and respect the unique skills and personalities of the whole team." (Horswill 2007) Given the importance of building a common identity, social identity research offers insight into the potential value of creating a common ingroup identity to override potentially fragmenting identities.

The large body of empirical work on social identity throughout the social sciences has established several robust findings regarding the development of a group identity and its effects. Most fundamentally, the research shows that group identity affects individual behavior. For example, Tajfel, Billig, Bundy and Flament (1971) find that group membership creates ingroup enhancement in ways that favor the ingroup at the expense of the outgroup. Additionally, many experiments in social psychology identify factors which enhance or mitigate ingroup favoritism. Furthermore, as a person derives self-esteem from the group membership she identifies with (McDermott forthcoming), salient group identity induces people to conform to stereotypes (Shih, Pittinsky and Ambady 1999).

Since the seminal work of Akerlof and Kranton (2000), there has been increased interest in social identity research in economics, yielding new insights into phenomena which standard economic analysis on individual-level incentives proves unable to explain. Social identity models have been applied to the analyses of gender discrimination, the economics of poverty and social exclusion, the household division of labor (Akerlof and Kranton 2000), the economics of education (Akerlof and Kranton 2002), contract theory (Akerlof and Kranton 2005), economic development (Basu 2006), public goods provision (e.g., Croson, Marks and Snyder (2008), Eckel and Grossman (2005)), and the political economy of income redistribution (Shayo forthcoming).

In their preference-based models, Akerlof and Kranton (2000) propose a neoclassical utility function, where identity is associated with different social categories and exogenous behavioral prescriptions. In these models, deviations from the prescription cause disutility.[1] When this utility function is applied to contract theory (Akerlof and Kranton 2005), an agent who identifies with the firm is assumed to have a behavioral prescription to exert high effort, while an agent who does not

[1]Benabou and Tirole (2007) present an alternative theoretical framework, which emphasizes the management of beliefs and the cognitive mechanisms leading to identity investments.

is assumed to have a behavioral prescription to exert low effort. For wider applications of preferences incorporating social identity, it is important to endogenize such behavioral prescriptions. In his presidential address to the American Economic Association, Akerlof (2007) proposes that "the incorporation of such endogeneity is the next step" in social identity research. One way to endogenize such behavioral norms is to include social identity as a part of an individual's group-contingent social preference. We are aware of three such extensions of social preference models. First, Basu (2006) uses an altruism model where the weight on the other person's payoff is independent of payoff distributions to derive conditions for cooperation in the Prisoner's Dilemma game. In comparison, McLeish and Oxoby (2007) and Chen and Li (2009) both incorporate social identity as part of an individual's difference-averse social preference, extending the piece-wise linear models of Fehr and Schmidt (1999) and Charness and Rabin (2002). In this paper, we apply the group-contingent social preference model to the class of potential games with multiple Pareto-ranked equilibria.

This class of games is a challenging domain for economic models of social identity, as "predicting which of the many equilibria will be selected is perhaps the most difficult problem in game theory" (Camerer 2003). Using a group-contingent social preference model, we derive the conditions under which social identity changes equilibrium selection in the class of potential games with multiple Pareto-ranked equilibria, which includes the minimum effort games of Van Huyck, Battalio and Beil (1990). We then use laboratory experiments to verify the theoretical predictions. The results show that, under parameter configurations where learning would result in convergence to the inefficient, low-effort equilibrium (Goeree and Holt 2005), an induced salient group identity can lead to ingroup coordination to the efficient high-effort equilibrium. Thus, our work demonstrates that modeling social identity as group-contingent social preference endogenizes the behavioral prescriptions described in the Akerlof and Kranton model. Furthermore, we show that, at least for the class of potential games, social identity changes equilibrium behavior by changing the potential function.

Our findings contribute to the experimental economics literature, where the fact that social norms, group identity or group competition can lead to a more efficient equilibrium has been demonstrated in the context of the minimum effort game (e.g., Weber (2006), Bornstein, Gneezy and Nagel (2002)), the provision point mechanism (Croson et al. 2008) and the Battle of Sexes (Charness, Rigotti and Rustichini 2007). Our theoretical model provides a unifying framework for understanding these experimental results.

The rest of the paper is organized as follows. Section 2 reviews the main experimental and theoretical results on the minimum effort games. In Section 3, we present the theory of potential games, incorporate social identity into the potential function, and derive theoretical predictions. In Section 4, we present our experimental design. Section 5 presents our hypotheses. Section 6 presents the analysis and results. Section 7 uses the potential games framework to reconcile the experimental findings of the effects of groups and group identity on equilibrium selection. Section 8 concludes.

2 The Minimum Effort Coordination Game

The minimum effort game is among the most well known of coordination games, with multiple Pareto-ranked equilibria. Rather than exhaustively reviewing the large experimental economics literature on coordination games,[2] we summarize the main findings for the minimum effort games, leaving a more thorough discussion of the literature on the effects of social identity and group competition on equilibrium selection to Section 7.

The general form of the payoff function for a player i in an n-person minimum effort game is as follows:

$$\pi_i(x_1, \ldots, x_n) \quad = \quad a \cdot \min\{x_1, \ldots, x_n\} - c \cdot x_i + b, \tag{1}$$

where a, c and b are real, non-negative constants, and $x_i \geq 0$ is the effort provided by player i. This game has multiple Pareto-ranked pure-strategy Nash equilibria. Specifically, any situation where every player provides the same effort level is a Nash equilibrium, and any equilibrium where the chosen effort is higher Pareto-dominates any equilibrium where the chosen effort is lower.

The most widely-cited paper in coordination games is the experimental test of the minimum effort game by Van Huyck et al. (1990), frequently shortened to VHBB. They conduct three treatments, all of which use the parameters $a = 0.2$ and $b = 0.6$. In the first treatment, $c = 0.1$ and the number of players in each game, n, ranges from 14 to 16. Subjects could choose any integer effort level from 1 to 7. After 10 rounds of this game, the subjects mostly converge to providing the lowest effort level of 1. In the second treatment, when n is reduced to 2, VHBB find that subjects converge to providing the highest effort level of 7. In a third treatment, n again ranges from 14 to 16, but the cost of providing effort is reduced to zero ($c = 0$). In this case, where offering the highest effort is a weakly dominant strategy for each subject, VHBB find that the subjects again converge to providing the highest effort level. These results suggest that whether group members exert high effort is sensitive to group size (n), the marginal benefit of the public good (a), and the individual marginal cost of effort (c).

Two streams of theoretical work explore the observed equilibria from the order-statistic coordination experiments, with the minimum effort game as a special case. In the first, Crawford and coauthors use learning dynamics, including evolutionary dynamics (Crawford 1991) and history-dependent adaptive learning models (Crawford 1995, Crawford and Broseta 1998) to track behavior in the experimental data. In comparison, Monderer and Shapley (1996) note that the minimum effort game is a potential game,[3] and that the empirical regularities from VHBB are consistent with the maximization of the potential function. Intuitively, the potential maximizing equilibrium has the largest basin of attraction under adaptive learning dynamics. Thus, both streams of theoretical work use learning dynamics to predict which equilibrium will be selected empirically.

While maximization of the standard potential yields a Nash equilibrium, experimental data are often noisy and better explained by statistical equilibrium concepts such as the quantal response equilibrium (McKelvey and Palfrey 1995). Motivated by this consideration, Anderson, Goeree and Holt (2001) derive the logit equilibrium prediction for the minimum effort game and show that the logit equilibrium maximizes the stochastic potential of the game. To test the theoretical predictions of the logit equilibrium, Goeree and Holt (2005) design a version of the minimum effort game with a continuous strategy space, where the subjects can choose any real effort level from 110 to 170. They use the parameters $a = 1, b = 0, n = 2$, i.e.,

$$\pi_i(x_i, x_j) = \min\{x_i, x_j\} - c \cdot x_i. \tag{2}$$

[2]We refer the reader to the excellent surveys of Ochs (1995) and chapter 7 of Camerer (2003) for an overview of the literature.

[3]We introduce potential games in Section 3

With these parameter values, the authors show that, consistent with the logit equilibrium prediction, when $c = 0.25$ subjects converge to an effort level close to 170, and when $c = 0.75$ subjects converge to an effort level close to 110. Our experimental design, described in Section 4, follows Goeree and Holt's, with the addition of induced group identities to test the effect of group identity on equilibrium selection.

3 Potential Games

Both theoretical and experimental studies of coordination games point to the importance of learning dynamics in equilibrium selection. Thus, we consider the dynamics of subjects' effort choices as the game is played repeatedly with different matches. When incorporating dynamic learning models, it is useful to examine the potential function of the game, as described by Monderer and Shapley (1996) and defined below. As Monderer and Shapley note, the minimum effort game is a potential game, in that it yields a potential function. One interesting property of potential games is that several learning algorithms converge to the argmax set of the potential, including a log-linear strategy revision process (Blume 1993), myopic learning based on a one-sided better reply dynamic and fictitious play (Monderer and Shapley 1996). Under these learning dynamics, the potential-maximizing equilibrium has the largest basin of attraction. It is for this reason that we study the potential function of the minimum effort game.

Monderer and Shapley (1996) formally define *potential games* as games that admit a potential function P such that:

$$\pi_i(x_i, x_{-i}) \geq \pi_i(x_i^{'}, x_{-i}) \quad \Leftrightarrow \quad P(x_i, x_{-i}) \geq P(x_i^{'}, x_{-i}), \quad \forall i, x_i, x_i^{'}, x_{-i}. \tag{3}$$

For differentiable games, P is a potential if and only if:

$$\frac{\partial \pi_i(x_i, x_{-i})}{\partial x_i} = \frac{\partial P(x_i, x_{-i})}{\partial x_i}, \quad \forall i, x_i, x_{-i}.$$

When the payoff functions are twice continuously differentiable, Monderer and Shapley (1996) present a convenient characterization of potential games. That is, a game is a potential game if and only if the cross partial derivatives of the utility functions for any two players are the same, i.e.,

$$\frac{\partial^2 \pi_i(x_i, x_{-i})}{\partial x_i \partial x_j} = \frac{\partial^2 \pi_j(x_j, x_{-j})}{\partial x_i \partial x_j}, \quad \forall i, j \in N.$$

As noted by Monderer and Shapley (1996), the minimum effort game with a payoff function defined by Equation (1) is a potential game with the potential function:

$$P(x_1, \ldots, x_n) = a \cdot \min\{x_1, \ldots, x_n\} - c\sum_{i=1}^{n} x_i. \tag{4}$$

In most previous experiments using the minimum effort game, subjects converge or begin to converge towards the equilibrium that maximizes the potential function.[4] Let the threshold marginal cost be $c^* = a/n$. When $c > c^*$, subjects converge to the least efficient equilibrium. Examples of this convergence include the VHBB treatment with parameters $a = 0.2$, $c = 0.1$, and

[4] We discuss the representative experiments and exceptions in Section 7.

$14 \leq n \leq 16$, and the $c = 0.75$ treatment in Goeree and Holt (2005). When $c < c^*$, subjects converge to the Pareto dominant equilibrium. Examples of this convergence include the VHBB treatment with $c = 0$, and the $c = 0.25$ treatment in Goeree and Holt (2005).

We next incorporate social identity into players' social preferences to demonstrate how identity can change equilibrium selection by changing the potential function. Let $g \in \{I, O, N\}$ be an indicator variable denoting whether the other player is an ingroup, outgroup or group-neutral match.

We use a group-contingent social preference model similar to those of Basu (2006), McLeish and Oxoby (2007) and Chen and Li (2009), where an agent maximizes a weighted sum of her own and others' payoffs, with weighting dependent on the group categories of the other players. In the n-player case, player i's utility function is a convex combination of her own payoff and the average payoffs of the other players,[5]

$$u_i(x) = \alpha_i^g \cdot \bar{\pi}_{-i} + (1 - \alpha_i^g) \cdot \pi_i(x) = \min\{x_1, \cdots, x_n\} - c \cdot [\alpha_i^g \cdot \bar{x}_{-i} + (1 - \alpha_i^g) \cdot x_i], \quad (5)$$

where $\alpha_i^g \in [-1, 1]$ is player i's group-contingent other-regarding parameter, $\bar{\pi}_{-i} = \sum_{j \neq i} \pi_j(x)/(n-1)$ is the average payoff of the other players, and $\bar{x}_{-i} = \sum_{j \neq i} x_j/(n-1)$ is the average effort of the other players. Based on estimations of α_i^g from Chen and Li (2009), we expect that $\alpha_i^I > \alpha_i^N > \alpha_i^O$. The transformed game with a utility function defined by Equation (5) is a potential game, which admits the following potential function,

$$P(x_1, \cdots, x_n) = \min\{x_1, \cdots, x_n\} - c \sum_{i=1}^{n} (1 - \alpha_i^g) x_i. \quad (6)$$

Note that the Nash equilibria for the transformed game defined by (5) remain the same as those in the original minimum effort game in Goeree and Holt (2005), as long as $c < \frac{1}{1-\alpha_i^g}$, for all i. We now use this formulation to derive a set of comparative statics results, which underscore the effects of group identity on equilibrium selection and form the basis for our experimental design. We present the propositions in this section and relegate all proofs to Appendix A.

Proposition 1. *Ingroup matching increases the threshold marginal cost, c^*, compared to outgroup or group-neutral matching. Furthermore, a more salient group identity increases c^*.*

Proof: See Appendix A. ∎

Proposition 1 implies that, under parameter configurations where the theory predicts convergence to a low-effort equilibrium when players have no defined group identity, an induced or enhanced group identity can raise the threshold marginal cost level and thus lead to the selection of a high-effort equilibrium. In our experimental design, we use the parameter configurations in Goeree and Holt (2005) where the marginal cost of effort is above the threshold, i.e., $c > c^*(n, \{\alpha_i^N\}_{i=1}^n)$, and where play converges close to the low-effort equilibrium, and investigate whether induced group identity can lead to convergence to the high-effort equilibrium.

[5]Key social preference models include Rabin (1993), Levine (1998), Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Charness and Rabin (2002), Falk and Fischbacher (2006), and Cox, Friedman and Gjerstad (2007), etc. Chen and Li (2009) extend the linear model of Charness and Rabin (2002) to incorporate social identity, while Chen and Li (2008) estimate a CES function of social identity and social preferences. We use a linear model here for simplicity.

While maximization of the standard potential yields a Nash equilibrium, experimental data are often noisy and better explained by statistical equilibrium concepts. Motivated by this consideration, Anderson et al. (2001) derive the logit equilibrium prediction for the minimum effort game and show that the predicted average efforts are remarkably close to the data averages in the final periods.

We now derive the logit equilibrium predictions for the transformed minimum effort game with a group-dependent other-regarding utility function as defined by Equation (5). Based on the standard assumption of the logit model that payoffs are subject to unobserved shocks from a double-exponential distribution, player i's probability density is an exponential function of the expected utility, $u_i^e(x)$,

$$f_i(x) = \frac{\exp(\lambda u_i^e(x))}{\int_{\underline{x}}^{\bar{x}} \exp(\lambda u_i^e(s))ds}, \quad i = 1, \cdots, n,$$

where $\lambda > 0$ is the inverse noise parameter and higher values correspond to less noise. As $\lambda \to +\infty$, the probability of choosing an action with the highest expected utility goes to 1. As $\lambda \to 0$, the density function becomes uniform over its support and behavior becomes random.

The logit equilibrium is a probability density over effort levels. As the characterization of the logit equilibrium for the transformed minimum effort game follows from Anderson et al. (2001), we summarize its properties in the following proposition without presenting the proof.

Proposition 2. *There exists a logit equilibrium for the extended minimum effort game with social identity. Furthermore, the logit equilibrium is unique and symmetric across players.*

Using symmetry and further assuming $\alpha_i = \alpha$ for all i, we first derive the equilibrium distribution of efforts.

Proposition 3. *The equilibrium effort distribution for the logit equilibrium is characterized by the following first-order differential equation:*

$$f(x) = f(\underline{x}) + \frac{\lambda}{n}[1 - (1 - F(x))^n] - c(1 - \alpha)\lambda F(x). \tag{7}$$

Proof: See Appendix A. ∎

Equation (7) plays a key role in both our comparative statics results and our data analysis. We compute the logit equilibrium effort distribution in Section 4 as a benchmark for the final-rounds analysis in Section 6. Anderson et al. (2001) prove that increases in the marginal cost, c, or the number of players, n, result in lower equilibrium effort in the sense of first-order stochastic dominance. Similarly, using (7), we next characterize the effect of group-contingent social preference on equilibrium selection.

Proposition 4. *Increases in the group-contingent social preference parameter, α, result in higher equilibrium effort (in the sense of first-order stochastic dominance).*

Proof: See Appendix A. ∎

If players are more altruistic towards their ingroup members than towards outgroup members, i.e., $\alpha^I > \alpha^N > \alpha^O$, Proposition 4 implies that the distribution of effort under ingroup matching first-order stochastically dominates that under group-neutral matching, which, in turn, first-order stochastically dominates that under out-group matching, i.e., $F^I(x) \leq F^N(x) \leq F^O(x)$.

Consequently, the average equilibrium effort is the highest with ingroup matching, followed by group-neutral and then outgroup matching.

Lastly, as a limit result, we note that the equilibrium density converges to a point mass as the noise goes to zero, which coincides with the predictions of potential maximization.

Proposition 5. *When the inverse of the noise parameter, λ, goes to infinity, the equilibrium density converges to a point mass at the maximum effort $\bar{x}$ if $c < c^*$, at $(\bar{x} - \underline{x})/n$ if $c = c^*$, and at the minimum effort $\underline{x}$ if $c > c^*$, where $c^* = 1/[n(1-\alpha)]$.*

Proof: See Appendix A. ∎

Together, Propositions 1, 3, 4 and 5 form the basis for our experimental design and hypotheses, which we present in the next two sections.

4 Experimental Design

We design our experiments to determine the effects of group identity on equilibrium selection, to test the comparative statics results from Section 3, and to investigate the interactions of group identity and learning. We now present the economic environments and our experimental procedure.

4.1 Economic Environments

To study equilibrium selection, we use the same payoff parameters as those of the two-person treatment in Goeree and Holt (2005). However, since our main interest is to investigate the effects of group identity on equilibrium selection, we induce group identities in the lab before the subjects play the minimum effort game. Furthermore, we run longer repetitions to study the effects of learning dynamics.

Within our experiments, the payoff function, in tokens, for a subject i matched with another subject j is the following:

$$\pi_i(x_i, x_j) \quad = \quad \min\{x_i, x_j\} - 0.75 \cdot x_i, \tag{8}$$

where x_i and x_j denote the effort levels chosen by subjects i and j, respectively; each can be any number from 110 to 170, with a resolution of 0.01. By Equation (4), the threshold marginal cost of effort, c^*, is equal to 0.5. Therefore, absent of group identities, we expect subjects to converge close to the lowest effort level, 110, which is confirmed by Goeree and Holt (2005).

With group-contingent social preferences, however, the potential function for this game becomes

$$P(x_i, x_j) \quad = \quad \min\{x_i, x_j\} - 0.75 \cdot [(1-\alpha_i^g)x_i + (1-\alpha_j^g)x_j], \tag{9}$$

where α_i^g is the weight that a subject places on her match's payoff. Proposition 5 implies that, in the limit with no noise, this potential function is maximized at the most efficient equilibrium if $\alpha^g > \frac{1}{3}$, and at the least efficient equilibrium if $\alpha^g < \frac{1}{3}$. Proposition 4 implies that, with sufficiently strong group identities, ingroup matching leads to a higher average equilibrium effort than either outgroup matching or control (non-group) matching.

4.2 Experimental Procedure

A key design choice for our experiment is whether to use participants' natural identities, such as race and gender, or to induce their identities in the laboratory. Both approaches have been used in lab settings. However, because of the multi-dimensionality of natural identities which might lead to ambiguous effects in the laboratory, we induce identity, which gives the experimenter greater control over the participant's guiding identity.

Our experiment follows a 2×3 between-subject design. In one dimension, we vary the strength of group identity, with near-minimal-group and enhanced treatments. Our near-minimal-group treatment is so named because it implements groups in a way that is nearly minimal. The criteria for *minimal groups* (Tajfel and Turner 1986) are as follows:

1. Subjects are randomly assigned to groups based on a trivial task.
2. Subjects do not interact.
3. Group membership is anonymous.
4. Subjects' choices do not affect their own payoffs.

Our near-minimal treatments achieve the first three of these four criteria, as subjects are assigned to groups based on the random choice of an envelope with a certain colored card inside, and are not allowed to speak to one another or open their envelopes in public. The fourth criterion cannot be realistically achieved in most economics experiments since subjects' monetary payoffs are usually tied to their choices. Since this criterion is not met, we refer to these treatments as *near minimal*.

Past experimental research finds that the extent to which induced identity affects behavior depends on the strength or salience of the social identity. For example, Eckel and Grossman (2005) use induced team identity to study the effects of identity strength on cooperative behavior in a repeated VCM game. They find that "just being identified with a team is, alone, insufficient to overcome self-interest." However, actions designed to enhance team identity, such as group problem solving, contribute to higher levels of team cooperation. Similar findings on the effect of group salience are reported in Charness et al. (2007). In our near-minimal treatments, subjects are first randomly assigned to groups, and then play the minimum-effort game for 50 rounds. By contrast, in our enhanced treatments, after being randomly assigned to groups, subjects are asked to solve a problem about a pair of paintings. They can use an online chat program to discuss the problem with other members of their group. This problem-solving stage is designed to enhance group identity.

To minimize experimenter demand effects, we use a between-subject design. For treatment sessions, each subject is in either an ingroup session where she is always matched with a member of her own group, or an outgroup session where she is always matched with a member of the other group. To control for the time between group assignment and the minimum effort games, we use two different controls, one for the near-minimal treatments, and one for the enhanced treatments.[6] In the former, subjects play the minimum effort game without being assigned to groups. In the latter, each subject is asked to solve the same painting problem on their own, without the online chat.

Our experimental process is summarized as follows:

[6] Chen and Li (2009) note that group effect induced by categorization deteriorates over time in their experiment. Therefore, it is important to control for the time between categorization and the minimum effort game in the treatment and the corresponding control.

1. Random assignment to groups: Every session has twelve subjects. In the treatment sessions, each subject randomly chooses an envelope which contains either a red or a green index card with a subject ID number on it. The subject is assigned to the Red or the Green group based on this index card; each group has six members. In the control sessions, there is no assignment into different groups. Instead, each subject randomly chooses an envelope which contains a white index card with a subject ID number on it.

2. Problem-solving: In the enhanced treatments and their corresponding control sessions, the subjects are asked to solve a problem. First, subjects are given five minutes to review five pairs of paintings each of which contains one painting by Paul Klee and one painting by Wassily Kandinsky. The subjects are also given a key indicating which of the two artists painted each of the ten paintings.[7] Next, subjects are shown two final paintings, each of which was painted by either Klee or Kandinsky. The subjects are then asked to determine, within ten minutes, which artist painted each of these final two paintings.[8] In the treatment sessions, each subject is allowed to use an online chat program to discuss the problem with other members of her own group. A subject is not required to give answers that conform to any decision reached by her group, and she is not required to contribute to the discussion. In comparison, subjects in the corresponding control sessions are given the same amount of time to solve the painting problem on their own, without the online chat option. For each correct answer, a subject earns 350 tokens (the equivalent of $1).[9] Note that the near-minimal treatments and the corresponding control sessions do not contain this stage.

3. Minimum effort game: Each subject plays the minimum effort game 50 times. For each round, each subject is randomly re-matched with one other subject in the same session. In the ingroup treatment sessions, subjects are matched only with members of their own group. In outgroup treatment sessions, subjects are matched only with members of the other group. In the control sessions, there are no groups, so subjects can be matched with any other person in the same session.

4. Survey: At the end of each experimental session, subjects fill out a post-experiment survey which contains questions about demographics, past giving behavior, strategies used during the experiment, group affiliation, and prior knowledge about the artists and paintings.

[Table 1 about here.]

Table 1 summarizes the features of the experimental sessions. In each of the four treatments and two corresponding controls, we run three independent sessions, each with 12 subjects. Overall,

[7]All paintings in this experiment are the same as those used in Chen and Li (2009). The five pairs of paintings are: 1A *Gebirgsbildung*, 1924, by Klee; 1B *Subdued Glow*, 1928, by Kandinsky; 2A *Dreamy Improvisation*, 1913, by Kandinsky; 2B *Warning of the Ships*, 1917, by Klee; 3A *Dry-Cool Garden*, 1921, by Klee; 3B *Landscape with Red Splashes I*, 1913, by Kandinsky; 4A *Gentle Ascent*, 1934, by Kandinsky; 4B A *Hoffmannesque Tale*, 1921, by Klee; 5A *Development in Brown*, 1933, by Kandinsky; 5B *The Vase*, 1938, by Klee.

[8]Painting #6 is *Monument in Fertile Country*, 1929, by Klee, and Painting #7 is *Start*, 1928, by Kandinsky.

[9]In the enhanced treatment sessions, 83.3% of the participants provided correct answers to both paintings, 9.7% provided one correct answer, and 6.9% provided zero correct answers. In the enhanced control sessions, 66.7% of the participants provided correct answers to both paintings, 19.4% provided one correct answer, and 13.9% provided zero correct answers. The average number of correct answers is significantly higher in the enhanced treatment than in the enhanced control sessions ($p = 0.048$, one-tailed t-test).

18 independent computerized sessions were conducted in the Robert B. Zajonc Laboratory at the University of Michigan between October 2007 and May 2008, yielding a total of 216 subjects. All sessions were programmed in z-Tree (Fischbacher 2007). Nearly all of our subjects were drawn from the student body of the University of Michigan.[10] Subjects were allowed to participate in only one session. Each enhanced session lasted approximately one hour, whereas each near-minimal session lasted about forty minutes. The exchange rate was set to 350 tokens for $1. In addition, each participant was paid a $5 show-up fee. Average earnings per participant were $10.82 for those in the near-minimal sessions and $11.69 for those in the enhanced sessions. The experimental instructions are included in Appendix B, while the survey and response statistics are included in Appendix C. Data are available from the authors upon request.

5 Hypotheses

In this section, we present our hypotheses regarding subject effort in the minimum effort game as related to group identity. Our general null hypothesis is that behavior does not differ between any pair of treatments.

HYPOTHESIS 1 (Effect of Groups on Effort Choices: Ingroup vs. Control)**.** *The average effort level in the ingroup treatment is greater than that in the control sessions:* $\bar{x}^I > \bar{x}^N$.

HYPOTHESIS 2 (Effect of Groups on Effort Choices: Ingroup vs. Outgroup)**.** *The average effort level in the ingroup treatment is greater than that in the outgroup treatment:* $\bar{x}^I > \bar{x}^O$.

HYPOTHESIS 3 (Effect of Groups on Effort Choices: Control vs. Outgroup)**.** *The average effort level in the control sessions is greater than that in the outgroup treatment:* $\bar{x}^N > \bar{x}^O$.

These hypotheses are based on Proposition 4. As α^g increases, the stochastic choice function shifts the probability weight from lower effort to higher effort. Since we expect $\alpha^I > \alpha^N > \alpha^O$, we expect subjects in the ingroup sessions to choose higher effort than those in control sessions, and subjects in the control sessions to choose higher effort than those in the outgroup sessions.

Furthermore, when we enhance the groups, we expect the effect on α^g to be more extreme, so $\alpha^{EI} > \alpha^{MI}$ and $\alpha^{EO} < \alpha^{MO}$, where EI (MI) stands for "enhanced (near-minimal) ingroup" and EO (MO) stands for "enhanced (near-minimal) outgroup." Thus, we obtain the following hypotheses on the effect of identity salience.

HYPOTHESIS 4 (Effect of Identity Salience on Effort Choices: Ingroup)**.** *The average effort level in the enhanced ingroup treatment is greater than that in the near-minimal ingroup treatment:* $\bar{x}^{EI} > \bar{x}^{MI}$.

HYPOTHESIS 5 (Effect of Identity Salience on Effort Choices: Outgroup)**.** *The average effort level in the enhanced outgroup treatment is less than that in the near-minimal outgroup treatment:* $\bar{x}^{EO} < \bar{x}^{MO}$.

An additional measure of interest in our experiment is efficiency. We define a normalized efficiency measure following the convention in experimental economics:

$$\text{Efficiency} = \frac{\text{Total Payoff - Minimal Payoff}}{\text{Maximal Payoff - Minimal Payoff}},$$

[10] One subject was from Eastern Michigan University, and one subject was not affiliated with a school.

where Total Payoff is the total amount earned by two subjects in a match; Minimal Payoff (10) is the minimum possible total amount that can be earned between two subjects in a match, achieved if one subject chooses an effort of 110, and the other chooses an effort of 170; and Maximal Payoff (85) is the maximum possible total amount that can be earned between two subjects in a match, achieved if both subjects choose an effort of 170. With this definition, efficiency can be any value from 0 to 1, with 0 denoting the case where subjects earn the minimum possible total payoff, and with 1 denoting the case where subjects earn the maximum possible total profit.

We use the equilibrium distribution described in Equation (7) to compute the expected effort and efficiency for different values of α. For each distribution, we assume that $\lambda = 0.125$, the value estimated by Goeree and Holt (2005). Summary statistics of this distribution for various values of α are included in Table 2.

[Table 2 about here.]

This table shows that the expected efficiency depends non-monotonically on the exact level of α. As α increases from -1, the expected efficiency decreases until α reaches 0, then increases until α reaches 1. Given the above definition of efficiency, this behavior is expected. That is, at low values of α, subjects mostly give low effort. This results in a medium level of efficiency. At high values of α, subjects give high effort, resulting in a high level of efficiency. The lowest level of efficiency should be achieved when subjects giving low effort are paired with subjects giving high effort. This occurs more frequently when α is not extreme.

6 Results

In this section, we first present our main results for the effects of group identity on equilibrium selection. We then present our analysis of the interaction of learning and group identity.

Several common features apply throughout our analysis and discussion. First, standard errors in the regressions are clustered at the session level to control for the potential dependency of decisions across individuals within a session. Second, we use a 5% statistical significance level as our threshold (unless stated otherwise) to establish the significance of an effect.

6.1 Group Identity and Effort

In this experiment, we are interested in whether social identity increases chosen effort. Figure 1 presents the minimum, median (solid lines) and maximum efforts in the near-minimal (top panel) and enhanced (bottom panel) group treatments.

[Figure 1 about here.]

Our first observation is that the time-series effort levels in the control sessions move towards the lowest effort, with a fairly widespread distribution in round 50. This is consistent with the prediction of the stochastic potential theory and replicates the findings from the two-person, high-cost treatment in Goeree and Holt (2005).[11] However, when group identity is induced, 8 out of 12

[11] Using two-sided Kolmogorov-Smirnov tests of the equality of distributions for last round choices, we find that the distribution of choices in our control sessions is not significantly different from that in the corresponding treatment in Goeree and Holt (2005) ($p = 0.170$, two-sided).

sessions show convergence towards the highest effort. In particular, all 3 sessions of the enhanced-ingroup treatment converge towards the highest effort. Group identity also seem to increase the effort level in the near-minimal treatments, but the effects are not as strong. We next use random-effects OLS regressions to investigate the significance of the observed patterns.

[Table 3 about here.]

In Table 3, we present two random-effects OLS regressions, one with and one without demographic variables included, with clustering at the session level. The dependent variable for these two regressions is the effort level chosen, while the independent variables for all regressions include dummy variables describing whether the subject participated in an ingroup or an outgroup session, with the control as the omitted group. Two other independent variables included in both regressions are the interaction terms between the matching scheme and a dummy variable for whether the session was an enhanced session. These two independent variables allow us to test the effect of group salience on effort level. For these regressions, we treat the two controls in our design (one for the near-minimal and one for the enhanced sessions) as the same group of sessions. The demographic variables include age and the following dummy variables (with omitted variables in parentheses): gender (male), race (Caucasian), marital status (single), employment status (unemployed), number of siblings (zero siblings), expenses (self), voting history (not a voter), and volunteer status (not a volunteer). The "expenses" variable captures the response to the question of who in the subject's household is responsible for the finances of the household (see Appendix C). In Table 3, we omit some demographic variables, but none that are significant, even at the 10% level. We summarize the results from Table 3 below.

Result 1 (Group effect on effort in near-minimal treatments)**.** *In the near-minimal sessions, participants in the different treatments do not choose significantly different effort levels.*

Support. *In Table 3, the coefficients for the ingroup dummies ($p = 0.217$ for (1) and $p = 0.407$ for (2)) and for the outgroup dummies ($p = 0.160$ for (1) and $p = 0.290$ for (2)) are not significant. A test of equality of the ingroup and outgroup dummies yields $p = 0.771$ for (1), and $p = 0.764$ for (2).* ■

Result 1 indicates that, in the near-minimal treatments, subjects in different sessions make roughly the same effort choices throughout the experiment. While the subjects in ingroup sessions provide a slightly higher level of effort than subjects in the control sessions (by 8.82 and 5.81 units of effort in (1) and (2), respectively), this amount is not significant. In fact, subjects in sessions where they are paired with people not in their own group provide an amount of effort that is even higher than that of subjects in the control sessions (10.76 and 7.89 more units, respectively). However, this difference is insignificant. Thus, this result fails to reject the null in favor of Hypotheses 1, 2, and 3 for the near-minimal treatments.

Result 2 (Group effect on effort in enhanced treatments)**.** *In the enhanced sessions, participants in the ingroup sessions choose significantly higher effort levels than those in the control and outgroup sessions, while participants in the control and outgroup sessions do not choose significantly different effort levels.*

Support. *A test that the sum of the coefficients on the ingroup dummy and ingroup-enhanced interaction term is equal to 0 yields $p < 0.0001$ for (1) and $p = 0.0003$ for (2), while a test that the previous sum is equal to the corresponding outgroup sum yields $p = 0.023$ for (1) and $p = 0.009$ for (2). A test that this outgroup sum is equal to 0 yields $p = 0.976$ for (1) and $p = 0.807$ for (2).* ■

Result 2 indicates that, in the enhanced treatments, subjects in the ingroup sessions provide significantly higher effort than subjects in the other sessions (by 24.20 in (1) and 21.06 units of effort in (2) compared to the control sessions, obtained by summing the coefficients on the ingroup dummy and the ingroup-enhanced interaction term). Subjects in the outgroup sessions provide approximately the same amount of effort compared to subjects in the control sessions (0.35 units more in (1) and 2.62 units fewer in (2)). By Result 2, we reject the null in favor of Hypotheses 1 and 2, but we fail to reject the null in favor of Hypothesis 3 for the enhanced treatments. Both of these results are consistent with those outlined in Brewer's (1999) survey of social psychology experiments relating to social identity. Brewer (1999) notes that ingroup favoritism does not have to be mirrored by outgroup discrimination. Here, we see a significant ingroup favoritism effect with no corresponding outgroup discrimination effect. However, this effect is only observed when group identity is sufficiently salient.

Result 3 (Effect of group salience on effort)**.** *When groups are more salient, participants in the ingroup sessions choose significantly higher effort levels, while those in outgroup sessions do not.*

Support. *In Table 3, the coefficients on the interaction terms between the ingroup dummy and the enhanced dummy are highly significant ($p = 0.001$ for both (1) and (2)), while the coefficients on the interaction terms between the outgroup dummy and the enhanced dummy are not significant ($p = 0.369$ for (1) and $p = 0.349$ for (2)).* ∎

Result 3 shows that subjects matched with salient ingroup members are more likely to exhibit a high effort than those matched with less-salient ingroup members (by 15.38 and 15.25 units of effort in (1) and (2), respectively). Also, subjects matched with salient outgroup members do not exhibit significantly less effort than subjects matched with less-salient outgroup members (they exhibit 10.41 and 10.51 fewer units of effort in (1) and (2), respectively). Therefore, we reject the null in favor of Hypothesis 4, but we do not reject the null for Hypothesis 5.

Overall, the effect of placing people into groups and then having them play a game with each other is to increase their group-contingent other-regarding parameter, α_i^g. In the control sessions, α_i^g is at its base level. In the ingroup sessions, we expect this value to increase; if the increase is great enough, then the potential-maximizing effort choice changes from the minimum effort to the maximum effort. In our experiments, the near-minimal ingroup sessions possibly increase α_i^g, but not enough to change the potential-maximizing effort. In addition, the purpose of the enhanced sessions is to further increase subjects' group-contigent other-regarding parameters. The results show that such a process increases α_i^g enough to also substantially increase the effort level chosen by the participants. In Subsection 6.3, we estimate the parameter α_i^g together with other parameters of the adaptive learning model described previously.

6.2 Equilibrium Play and Efficiency

[Figures 2 and 3 about here.]

In addition to examining the relation between group identity and effort, we also examine the degree of coordination subjects exhibit in the various treatments. Figure 2 shows the frequencies of the minimum effort levels chosen in each match for the first 10 (left column) and last 10 (right column) periods of each session. Figure 3 shows the frequencies of "wasted" efforts exhibited by each match for the first 10 (left column) and last 10 (right column) periods in each session.

Here, "wasted" effort is defined as the difference in the maximum effort chosen in a match and the minimum effort chosen in that match. Since subjects are paid only the minimum effort chosen in a match, if a subject provides more than the minimum effort, then that subject pays more but receives no extra benefit. This figure shows the degree of coordination that the matches exhibit. In Figure 3, matches with no wasted effort indicate subjects are in a Nash equilibrium. Conversely, matches with high levels of wasted effort indicate subjects do not coordinate to a Nash equilibrium. For both figures, the left columns show the first 10 periods while the right columns show the last 10 periods. The top rows show the near-minimal treatments while the bottom rows show the enhanced treatments.

Several results can be observed from these figures. First, for the first 10 periods in the near-minimal treatments, there is not much difference between the control, ingroup, and outgroup sessions in terms of minimum effort chosen or amount of wasted effort. Furthermore, both metrics seem to be uniformly distributed among the allowed values. In the enhanced treatments, the first 10 periods show that the subjects in ingroup sessions are more likely to give the maximum effort, and there is a much higher frequency of little to no waste, indicating a higher degree of equilibrium play than in the near-minimal treatments, the outgroup, or the control sessions.

However, as we move to the last 10 periods, several changes occur. First, in all treatments, the fraction of matches that have little to no wasted effort increases greatly. As the game is repeated 50 times, subjects learn to coordinate with their matches, and are more successful in doing so than in the first 10 periods. The most prominent difference between the near-minimal and enhanced treatments can be observed in the minimum efforts chosen in the last 10 periods. For the near-minimal treatments, subjects in non-control sessions are more likely to choose the highest effort level, as both the ingroup and outgroup treatments have modes at the highest minimum effort level of 165-170 (though the ingroup sessions also exhibit a mode at 140). In contrast, no match in the control sessions has a minimum effort of 165-170; instead, that frequency graph has modes at 125 and 140.

With the enhanced treatments, we get a more interesting result. For the ingroup treatments, the mode is clearly at 170. In fact, almost 60% of the matches have a minimum effort of 165-170. On the other hand, the control and outgroup sessions exhibit very similar bimodal frequency graphs, with many subjects choosing the lowest effort of 110 and the highest effort of 170. In the enhanced sessions, the learning that takes place during the sessions causes the subjects to move towards extreme effort levels, a phenomenon that is not necessarily seen in the near-minimal treatments.

We now use a probit regression to investigate the significance of the observed patterns. In Table 4, we present the results of this regression, reporting the marginal effects. The dependent variable is a dummy variable indicating whether each pair is in an equilibrium (i.e. whether the subjects in each pair choose the same level of effort). The independent variables are an ingroup dummy, an outgroup dummy, an ingroup-enhanced interaction term, and an outgroup-enhanced interaction term.

[Table 4 about here.]

The definitions of the independent variables are the same as described above for the effort choice regressions. We summarize the results from Table 4 above.

Result 4 (Group effect on coordination)**.** *In the near-minimal sessions, matches in the ingroup, outgroup, and control sessions coordinate to an equilibrium at about the same rate. In the enhanced sessions, matches in the ingroup sessions coordinate to an equilibrium significantly more* *often than subjects in the control or outgroup sessions while subjects in the outgroup sessions do so at about the same rate as those in the control sessions. Increased group salience significantly increases the rate of coordination in the ingroup treatment, but not in the outgroup treatment.*

Support. *In Table 4, neither the coefficient for the ingroup dummy (*$p = 0.186$*) nor that for the outgroup dummy (*$p = 0.821$*) are significant. A test of equality of the ingroup and outgroup dummies yields* $p = 0.270$*. The coefficient on the interaction term between the ingroup dummy and the enhanced dummy is significant (*$p = 0.023$*), while the coefficient on the interaction term between the outgroup dummy and the enhanced dummy is not significant (*$p = 0.918$*). A test that the sum of the coefficients of the ingroup dummy and the ingroup-enhanced interaction term is equal to 0 yields* $p = 0.0005$*, while a test that this sum is equal to the corresponding outgroup sum yields* $p = 0.0162$*. Finally, a test that this outgroup sum is equal to 0 yields* $p = 0.775$*.* ■

Result 4 indicates that pairs in different non-minimal treatments choose the same effort level at about the same rate. Both the near-minimal ingroup and near-minimal outgroup sessions produce slightly higher probabilities of matching effort (by 14% and 2% for the ingroup and outgroup sessions, respectively), but neither increase is statistically significant. The result also shows that pairs of salient ingroup members are significantly more likely to give equal efforts than pairs of less-salient ingroup members (by 21%). Also, pairs of salient outgroup members are equally likely to give equal efforts when compared to pairs of less-salient outgroup members (a 1% increase in effort matching). Finally, the result indicates that, if we examine only the enhanced treatments, subjects in the ingroup sessions choose the same effort more often than subjects in either the outgroup or control sessions. While subjects in the ingroup sessions choose the highest effort level of 170 nearly exclusively by the end of 50 periods, making the probability of obtaining an equilibrium result more likely, subjects in the outgroup and control sessions seem unable to decide whether to choose the lowest effort level of 110 or the highest effort level of 170 even after 50 periods. The minimum effort in each pair is 110 as often as it is 170, as shown in Figure 2. This result generally supports the predictions of the theoretical model.

[Table 5 about here.]

Next, we examine efficiency in each treatment, as defined in Section 5. Table 5 presents the average efficiency in each session and the overall efficiency in each treatment. While the overall efficiency levels in the near-minimal treatments are similar, the ingroup sessions in the enhanced treatment achieve much higher efficiency.

[Table 6 about here.]

To evaluate the statistical significance of our impressions from session averages, in Table 6, we present a random-effects OLS regression, with standard errors clustered at the session level. The dependent variable is the efficiency of each pair. The independent variables of the regression are the ingroup and outgroup dummy variables, and the ingroup-enhanced and outgroup-enhanced interaction terms.

Result 5 (Group effect on efficiency)**.** *In the near-minimal sessions, there is no significant difference in efficiency across the ingroup, outgroup and control treatments. In the enhanced sessions, efficiency in the ingroup treatment is significantly higher than that in the control and outgroup treatments. Increased group salience significantly increases efficiency in the ingroup treatment, but not in the outgroup treatment.*

Support. *In Table 6, neither the coefficient for the ingroup dummy ($p = 0.594$) nor that for the outgroup dummy ($p = 0.671$) is significant. A test of equality of the ingroup and outgroup dummies yields $p = 0.392$. The coefficient on the interaction term between the ingroup dummy and the enhanced dummy is significant ($p < 0.001$), while the coefficient on the interaction term between the outgroup dummy and the enhanced dummy is not significant ($p = 0.978$). A test that the sum of the coefficients of the ingroup dummy and the ingroup-enhanced interaction term is equal to 0 yields $p < 0.0001$, while a test that this sum is equal to the corresponding outgroup sum yields $p = 0.001$. Finally, a test that this outgroup sum is equal to 0 yields $p = 0.779$.* ∎

Result 5 shows that efficiency increases when subjects are matched with members of their own group, but only when groups are more salient. This finding is consistent with the predictions of the model in Table 2 (column 4), however, the predicted efficiency in Table 2, e.g., when α approaches 1, is generally lower compared to the actual achieved efficiency, e.g., in the enhanced ingroup treatment, in Table 5. This is because most of our subjects are able to coordinate on integer values while the computation reported in Table 2 assumes a continuous strategy space.[12] Subjects in the enhanced ingroup sessions, by coordinating on the highest effort level, are able to achieve much greater efficiencies than subjects in either the control or outgroup sessions. Coordination on the lowest effort level occurs in both the control and outgroup sessions, causing them to be fairly similar in terms of efficiency.

6.3 Learning Dynamics and Group Identity

While our reduced-form regression analysis establishes the significance of the effect of enhanced group identity on equilibrium selection, it does not demonstrate the reason behind this effect. In this subsection, we estimate a structural learning model and thus demonstrate the interaction between group identity and learning. In what follows, we first examine initial round choices and learning dynamics. We then estimate the parameters of the structural model and use these estimates to run a simulation. Finally, we compare choices in the final rounds with the predictions of our logit equilibrium model with calibrated parameters.

6.3.1 Initial Round

[Table 7 about here.]

We first examine whether any significant behavioral differences exist in the initial round choices. Using two-sided Kolmogorov-Smirnov tests of the equality of distributions for first-round effort choices (Table 7), we find that, within the near-minimal and enhanced treatments, only one of the pairwise comparisons is significantly different: near-minimal outgroup $\neq$ control ($p = 0.043$, two-sided). Likewise, comparing the near-minimal treatments with the corresponding enhanced treatments, only one of the pairwise comparisons is significantly different, and that only weakly: NM outgroup $\neq$ E outgroup ($p = 0.083$, two-sided).

Furthermore, we compare our initial round empirical distribution with both uniform and normal distributions, and find that we can reject that our empirical distribution follows either a uniform or a normal distribution ($p < 0.001$). Based on this analysis, we use the empirical distribution as the initial round belief of how an opponent will behave in our simulation of the learning model.

[12]Of all choices, 92.8-percent are integer choices.

6.3.2 Learning Dynamics: Stochastic Fictitious Play

In this subsection, we use a structural learning model to explain the effects of group identity on the dynamics and convergence to various equilibria of the minimum effort game. To do so, we look for a learning algorithm which incorporates key features of the adaptive learning models in the theoretical derivations (Monderer and Shapley 1996). A model which meets this criterion is the stochastic fictitious play model with discounting (Cheung and Friedman (1997), Fudenberg and Levine (1998)). Unlike the deterministic fictitious play used for the theoretical analysis in Monderer and Shapley (1996), the stochastic version allows decision randomization and thus better captures the human learning process. It also more closely follows our theoretical model, which uses decision randomization.

In our stochastic fictitious play model, player i holds a belief regarding her match's effort level x_j in every period t. We calculate this belief using a weight function $w_i^t(x_j)$. This weight function assigns to each of her match's possible effort levels a number which is positively correlated with the number of times she has seen her match give that level of effort in the past. She believes that the more times her match has given a particular effort level, the more likely it is that her match will give that effort level again. Note that for this analysis, we use a discrete strategy space. The initial value of this weight function is left unspecified by the model, giving $w_i^1(x_j)$. This function is then updated using the following rule:

$$w_i^{t+1}(x_j) = \delta \cdot w_i^t(x_j) + \begin{cases} 1 & \text{if } x_j = x^t \\ 0 & \text{otherwise,} \end{cases} \tag{10}$$

where x^t is the effort level exhibited by player i's match in period t, and δ is the discount factor. Player i's beliefs in period t are then calculated as follows:

$$\mu_i^t(x_j) = \frac{w_i^t(x_j)}{\sum_{x_j} w_i^t(x_j)}. \tag{11}$$

These beliefs are then be used to calculate player i's expected utility for playing a strategy x_i:

$$\overline{u}^t(x_i) = \frac{1}{(\overline{x} - \underline{x})} \sum_{x_j} [u_i(x_i, x_j) \cdot \mu_i^t(x_j)], \tag{12}$$

where $u_i(x_i, x_j)$ is as defined in Equation (5). We assume that all subjects in a given session have the same group-contingent other-regarding parameter, so $\alpha_i^g = \alpha^g \; \forall i$ in the same session.

Using this expected utility, player i randomly chooses an effort level x_i with a distribution defined by the following:

$$f_i^t(x_i) = \frac{\exp[\lambda \cdot \overline{u}^t(x_i)]}{\sum_{x_i} \exp[\lambda \cdot \overline{u}^t(x_i)]}, \tag{13}$$

where λ is the inverse noise level that describes how much randomization a player will employ. With this specification, as $\lambda \to 0$, the player uses full randomization, and as $\lambda \to \infty$, she plays her best response to her belief of what her match will play with probability 1. This model has three parameters: the sensitivity parameter λ, the discount factor δ, and the other-regarding parameter α^g.

6.3.3 Calibration

We next compare the observations from our experiment to the predictions of the above model. Performing a grid search over the three parameters, we calculate a score using the quadratic scoring rule described in Selten (1998) for each subject and round. In any given round, let $f_{ij} = (f_{i1}, \ldots, f_{iK})$ be the predicted probability distribution over player i's strategies, where K is the number of strategies available to the players, and $a_{ij} = (a_{i1}, \ldots, a_{iK})$ be the observed relative frequency distribution over player i's strategies, where $a_{ij} = 1$ if player i chooses action j, and zero otherwise. This score, $S_i(f)$, is calculated by:

$$S_i(f) = 1 - \sum_{j=1}^{K} (a_{ij} - f_{ij})^2.$$

Our estimates for the parameters are the values of λ, δ, and α^g that give the highest summed score in each session (over all subjects and rounds).

We allow λ to vary from 0 to 7 in increments of 0.1, δ to vary from 0 to 1 in increments of 0.1, and α^g to vary from -1 to 1 in increments of 0.01.[13] We perform this analysis at the session level. The calibration consists of the following steps:

1. First, we set all subjects' initial beliefs regarding their matches' first-period efforts to the empirical distribution of first period effort levels in the subjects' sessions. That is, we set $w_i^1(x_j)$ to the number of times the effort level, x_j, is used by any member of subject i's session (including subject i herself) in period 1.

2. For each subsequent period, we update a subject's beliefs based on the history of effort levels that the subject has observed from her matches, according to Equation (10).

3. For each period, given the subject's beliefs, we calculate the probability distribution of effort levels that the subject is predicted to play according to Equation (13).

4. Given this predicted distribution of effort levels, and the observed effort exhibited by the subject, we use a quadratic scoring rule to calculate a score for the particular combination of λ, δ, and α^g that we are examining. This gives us a score for each period the subject plays.

5. For each subject, we sum the period scores in order to obtain a score for that subject and that particular combination of λ, δ, and α^g.

6. For each session, we sum the subject scores in order to obtain a score for that session and that particular combination of λ, δ, and α^g. This score is recorded.

7. After we have completed this process for every combination of λ, δ, and α^g, we find the parameters that give the highest score in each session. These are the values that are reported in Table 8 in the "Near-Minimal" and "Enhanced" rows.

The results for the analysis are reported in Table 8 in the rows labeled "Near-Minimal" and "Enhanced," with treatment averages reported in the rows labeled "Average."

[13]The upper bound for λ is based on an initial exploration where we tested fewer values of λ over a larger range. As seen in Table 8, no session produced a λ that hit this upper bound.

[Table 8 about here.]

For our purposes, the most important parameter is α^g, which measures the level of group-contingent social preference. As expected, we see that the enhanced ingroup treatment obtains the highest average α^g, consistent with our effort and efficiency results. Also, every session of the enhanced ingroup treatment achieves a higher α^g than any session of the near-minimal control. Using a permutation test, this comparison (enhanced ingroup > near-minimal control) is marginally significant ($p = 0.0506$). The other comparisons are not significant since every other treatment has one session in which the subjects converge to the efficient equilibrium.

Using these parameter estimates, we next run simulations of the learning model in order to evaluate its accuracy.

6.3.4 Simulation

We compare a simulation using our estimated parameters with the observed subject actions. We perform this simulation on a session level, so every session is treated separately from the others. For each session, we track the beliefs and actions of the twelve simulated subjects. Also, we treat the parameter estimates as the actual parameters used by these simulated subjects to update their beliefs and choose their actions.

Our model is agnostic regarding the beliefs that the subjects hold and the actions that they choose in the first period of the game, so we use the empirical first-period actions in the model. Therefore, we assign the actual action of each subject to the subject's simulated counterpart for the first period. Also, we make each simulated subject's belief distribution in the first period equal to the empirical distribution of the first-period actions of the subjects in the session.

For subsequent periods, we use a one-period ahead version of the model to predict the actions that the subjects will take. Using a one-period ahead model allows us to use the entire empirical history of actions that the subjects observe in order to predict future actions. This is more realistic than a k-period ahead model, which uses predicted actions from previous periods to generate beliefs, since subjects make their decisions based on the entire history of opponent actions. Thus, our model's predictions are based on the same observables as those of the subjects.

For each period, we begin by updating the players' beliefs regarding what their matches will do in the next period. This is performed in the same way as described in step 2 of the calibration procedure. Specifically, we use only the empirical actions from previous periods to update these beliefs. By doing so, our model observes exactly what the subjects actually observed in the lab. Using this procedure, we build the distribution of effort levels the subject will choose based on the model, and use the distribution to randomly choose an effort. We repeat this process 70 times for each subject and period. The average effort plus and minus one standard deviation are plotted as solid lines in Figure 4. The actual choices by the subjects are also graphed as the black squares and error bars.

[Figure 4 about here.]

The simulation is qualitatively similar to the observed actions. In particular, the model is able to simulate the actions taken in the last few rounds. In Table 9, we report the Kolmogorov-Smirnov minimum distance statistic between each treatment and the corresponding simulation for the last 5 periods. For all but the enhanced outgroup treatment, there is no significant difference between the distribution of efforts from the simulation versus that from actual play. For the enhanced outgroup treatment, the difference between the distributions in the last period is significant at the 1% level. Since we cannot reject that the simulated and actual distributions are equal for most treatments, we take this as evidence that the calibrated model accurately describes actual behavior.

[Table 9 about here.]

6.4 Final Rounds

[Table 10 about here.]

To connect our learning model with the logit equilibrium model discussed earlier, we use the calibrated values of α^g from the learning model to compute theoretical distribution functions of effort choices in the logit equilibrium, i.e., Equation (7). We then compare the means and standard deviations of these theoretical distributions with the actual means and standard deviations of the effort choices in the last 5 rounds. We perform this analysis on a treatment level. These values are reported in Table 10. The means for the theoretical and actual distributions all fall within one standard deviation of each other, with the highest and lowest actual average efforts mirrored in the highest and lowest theoretical average efforts, respectively. We take this as a sign that the theoretical model performs well in describing the data in the final rounds.

7 Reconciling Theory and Experiments

In this section, we apply our theoretical framework to previous experimental studies on coordination games, including the minimum effort games, Battle of Sexes, and the provision point mechanism. By incorporating group identity into the potential games framework, we can reconcile findings from previous studies and thus showcase the applications of our theory.

[Table 11 about here.]

We first examine studies of the minimum effort games that are successful in achieving higher effort levels contrary to the predictions of the theory of potential games. A summary of these studies and the other studies of the minimum effort game mentioned in Section 2 is shown in Table 11.[14] In addition to the parameter configurations of each experiment (strategy space, T, n, a, b and c), the last three columns present the cutoff marginal cost c^*, the theoretical predictions from standard potential maximization, and the empirical trend observed in the experiment, respectively. Recall that standard potential maximization theory predicts that choices converge to the low (high) effort equilibrium if $c > c^*$ ($c < c^*$). This prediction is consistent with the results from the three baseline studies by Van Huyck et al. (1990), Goeree and Holt (2005), and Knez and Camerer (1994), as well as many treatments in subsequent categories. Whenever the theoretical prediction is inconsistent with the observed trend, we put the treatment in bold face. In what follows, we discuss the three approaches used in the literature to achieve higher effort levels contrary to the theoretical predictions and how incorporating group identity into the potential function could reconcile theory and the empirical findings (Propositions 1 and 4).

[14] Rather than exhaustively listing all experiments of the minimum effort games, we instead present representative studies in each category.

Over two papers, Camerer and Knez (1994 and 2000) show that, if they use the same parameters as VHBB ($a = 0.2, b = 0.6, c = 0.1$) in the minimum effort game, subjects will converge to the efficient equilibrium after 5 periods if $n = 2$, but not if $n = 3$. Using the phenomenon of "transfer of precedent," Camerer and Knez show that it is possible to make 3-player matches converge to the efficient equilibrium if the game is first played for 5 periods by 2-player matches with the third player observing, and then for 5 more periods with all 3 players. The 2-player matches establish a group norm of high effort that is consistent with potential theory, which is then transferred to the 3-player matches. Allowing the third player to watch the other 2 players for 5 periods implicitly creates a group, establishes a group norm, and increases subjects' other-regarding preferences.

Weber (2006) shows that it is possible to apply Camerer and Knez's result successively to achieve higher effort levels in larger groups. Using parameters similar to VHBB ($a = 0.2, b = 0.2, c = 0.1$), Weber slowly grows the number of players in the minimum effort game over 22 periods from $n = 2$ to $n = 12$. He shows that, if growth is too fast, or if no history is shown to the new players, then subjects converge to the least efficient equilibrium. If, on the other hand, the groups are grown slowly enough, and it is common knowledge that the new players observe the entire history of efforts provided, the entire 12-person group is able to achieve a minimum effort of 5 by the final period. Again, the observation of smaller groups facilitates the establishment of group norms.

Bornstein et al. (2002) use a different method, intergroup competition, to promote higher effort levels. Taking essentially the same game as VHBB ($a = 20, b = 60, c = 10$), Bornstein et al. divide subjects into two competing groups of size $n = 7$. The group with the higher chosen minimum effort level is paid according to the normal payoff function, while the group with the lower chosen minimum effort level is paid nothing (in the case of a tie, everyone is paid according to half the normal payoff function). This revised payment method changes the game. In particular, the set of Nash equilibria is expanded. It is still a Nash equilibrium for every member of both groups to give the same level of effort, but it is also a Nash equilibrium for the members of one group to all give the same effort, and two members of the other group to give a lower effort (the rest of the members of this other group can give any level of effort and still preserve the Nash equilibrium). While the potential function is also changed in this scenario, the potential maximizing Nash equilibrium remains the equilibrium in which every member of both groups gives the minimum possible effort of 1. So, if social preferences are ignored, then the prediction of potential theory is that players will converge to the least efficient equilibrium. In another treatment, the subjects are all paid according to the normal payoff function, but are also given the extra information of what the minimum effort level is in the other group (this information is withheld in the control). This separates the effect of receiving this information from the actual competition. While Bornstein et al. find that the extra information has no effect (the control yields an average effort of 3.6 while the information treatment yields an average effort of 3.5), there is a significant increase in chosen effort with intergroup competition (average effort 5.3). In another session, instead of punishing the losing group, the winning group receives a bonus. This yields an average effort of 4.5, also significantly higher than in the control or information sessions. By explicitly tying the subjects' payoffs to the choices of the group, and by making the 2 groups compete with each other, Bornstein et al. create a very strong ingroup and outgroup effect that is able to raise the threshold c^* above the marginal cost of 10 used in the experiment.

Another approach to increase effort is to facilitate communication across group members. Specifically, Chaudhuri, Schotter and Sopher (2009) suggest that giving subjects advice from previous subjects of the experiment can increase effort in large groups. Using the same parameters as VHBB and $n = 8$, the authors attempt to induce higher effort by providing subjects with full histories of previous sessions of the experiment, and by providing advice about the game given by previous subjects. Most of this advice suggests that players always give the highest effort. While this is not successful in most treatments, all of which have "private advice"(all subjects receive the advice but this is not common knowledge), the subjects do converge to the highest effort level when the advice is "public"(common knowledge). One plausible interpretation is that, communication between subjects creates an ingroup effect strong enough to induce high efforts, even if subjects in a session simply receive communication from a third party, as long as it is common knowledge that this communication is taking place.

Brandts and Cooper (2007) also examine the effect of communication in the minimum effort game. Communication in this study is achieved through a manager, who is the only subject allowed to talk to the other 4 subjects in a "firm." These 4 other subjects are workers of the firm who play a minimum effort game ($a = 6$ or $14, b = 200, c = 5$) with efforts restricted to 0, 10, 20, 30 or 40. The manager's payoff is also positively related to the minimum effort given by the 4 workers. Brandts and Cooper run three different treatments. In the first, the manager cannot communicate with the other subjects, but can control their financial incentives. In the second, managers can send messages to the other subjects (after the 10th period). This treatment is the most similar to the study run by Chaudhuri et al. The only difference here is that the third-party communicator has a stake in the game being played between the other players. In the third treatment, managers can send messages to other subjects and the subjects can send messages to the manager (also after the 10th period). The main result of this paper is that more avenues of communication lead to higher minimum effort levels. The two-way communication treatment yields higher minimum effort levels than the one-way communication treatment, and the same is true for the one-way communication treatment compared to the no-communication treatment. This result holds even when they consider only the sessions with minimum effort levels of 0 after the 10th period. The effect of communication in a coordination game may work through a different channel than other-regarding preferences, such as trust or learning (see Brandts and Cooper (2007) for a list, based on the content of the messages sent by the managers). However, discussions with the authors reveal that the most successful messages appeal to a group identity.

In addition to the minimum effort game, experimental studies of the provision point mechanism (PPM) indicate that competition between groups increases the likelihood of successful coordination to efficient equilibrium. The PPM is proposed by Bagnoli and Lipman (1989), with the property that it fully implements the core in undominated perfect equilibria in an environment with one private good and a single unit of public good.[15] In a complete information economy, agents voluntarily contribute any non-negative amount of the private good they choose and the social decision is to provide the public good if and only if contributions are sufficient to pay for it. The contributions are refunded otherwise. This mechanism has a large class of Nash equilibria, some of which are efficient while others not. Among a large number of experimental studies of this mechanism (see Chen (2008) for a survey), two studies highlight the effects of group competition in equilibrium selection, even though neither was explicitly designed to test group effects. First, Bagnoli and McKee (1991) study the mechanism with several independent groups simultaneously in the same room and publicly posted contributions for all groups. They find public good is provided in 86.7% of the rounds. Second, Mysker, Olson and Williams (1996) use the same parameters but with single, isolated groups. The latter is not nearly as successful as the former in

[15]With multiple discrete units, the theoretical results also hold, but there have been very few experimental studies of the multiple unit case.

coordinating to the efficient outcome. In the Bagnoli and McKee study, the efficient equilibrium contribution is a modal distribution, while in the Mysker, Olson and Williams study, contributions are evenly distributed along the strategy space. From the perspective of potential games, we can show that, in general, PPM is not a potential game.[16] However, with group competition, it can be transformed into a potential game where the potential maximizing equilibrium is the set of efficient equilibrium.

Another well-studied coordination game is the Battle of Sexes game (BoS hereafter). Charness et al. (2007) report a series of experiments on the effects of group membership on equilibrium selection in BoS games (as well as the prisoner's dilemma games). In treatments where groups are salient, the authors find that group membership significantly affects the rate of successful coordination. Taking a version of BoS such as the one on the left in the table below (Charness et al. 2007), it is straightforward to show that it is a potential game with the potential function given by $P = 4p_1p_2 - p_1 - 3p_2$, where p_i denotes the probability with which player i chooses A. Hence the potential is maximized by the mixed strategy equilibrium $(p_1 = 0.25, p_2 = 0.75)$. This prediction is consistent with the findings of Cooper, DeJong, Forsythe and Ross (1989), who show that subjects converge to a frequency of choices that is close to the mixed strategy equilibrium in BoS. If we transform the game to incorporate the effects of group identity, we obtain the game on the right, with the new potential function $P = 4(1+\alpha)p_1p_2 - (1+3\alpha)p_1 - (3+\alpha)p_2$, which is again maximized at its mixed strategy equilibrium. It is straightforward to show that the probability of coordination, $p_1p_2 + (1-p_1)(1-p_2)$, is increasing in α. This leads to a directional prediction that the probability of coordination is higher for ingroup matching compared to the control and outgroup matching, and increases with the salience of group identity.

Original BoS

	A	B
A	3, 1	0, 0
B	0, 0	1, 3

Transformed BoS

	A	B
A	3+α, 1+3α	0, 0
B	0, 0	1+3α, 3+α

In sum, we find that social identity, group competition, and group norms improve coordination in games with multiple Nash equilibria. Incorporating group identity into potential games provides a unifying framework which reconciles findings from a number of coordination game experiments.

8 Conclusion

In this paper, we study the effects of social identity on one of the most important and yet unresolved problems in game theory, the problem of equilibrium selection in games with multiple Nash equilibria. By incorporating group-contingent social preferences into Monderer and Shapley's theory of potential games, we make theoretical predictions on how and when salient group identities can influence equilibrium selection, and provide a unifying framework for a number of the previous experimental studies performed on coordination games.

To further test the ability of this model to predict behavior in an experimental setting, we design an experiment that uses induced group identity to increase group-contingent other-regarding preferences in the minimum effort games. In our near-minimal treatments, we show that, while

[16] A counter example can be constructed from an example used in Menezes, Monteiro and Temimi (2001). Let $x_i = \{0, c\}$. In the two-player case, $\pi_i(c,c) - \pi_i(c,0) - [\pi_i(0,c) - \pi_i(0,0)] = -v_i$, which violates the definition of potential games when $v_1 \neq v_2$.

matching subjects with ingroup or outgroup members when playing the minimum effort game has some effect on the effort levels chosen, they are not statistically distinguishable from the control, where no groups are induced. On the other hand, when we enhance the groups by allowing them to communicate with group members in solving a simple task before playing the minimum effort game, we find that matching subjects with ingroup members has a statistically significant positive effect on subject effort. When inducing groups, we find that it is only after the groups are made more salient that we see an effect on the provided effort. These findings are consistent with the predictions of our model.

In order to understand the mechanism through which this result is achieved, we incorporate group-contingent social preferences into a learning model of stochastic fictitious play. This enables us to specify the effect that creating groups and increasing their salience has on subjects' other-regarding preferences. The calibrated model also does well in predicting the empirical actions used by the subjects.

Our paper contributes to the theoretical foundations of social identity by demonstrating that, by using a simple group-contingent social preference model, we can endogenize the exogenous norms in the original Akerlof and Kranton model and reconcile the theory with experimental findings in a number of coordination games.

Beyond the fundamental problem of understanding and modeling identity on economic behavior, our results have practical implications for organizational design. As the world becomes more integrated, organizations are more frequently encountering the issue of integrating a diverse workforce, and motivating members from different backgrounds to work towards a common goal. Our paper demonstrates that creating a deep sense of common identity can motivate people to exert more effort to reach a more efficient outcome.

A successful application of this idea comes from Kiva (`http://www.kiva.org/`), a person-to-person microfinance lending site, which organizes loans to entrepreneurs around the globe. In August 2008, Kiva launched its lending teams program, which organizes lenders into identity-based teams. Any lender can join a team based on her school, religion, geographic location, sports, or other group affiliation. As of July 2009, the top five most successful teams are "the Atheists, Agnostics, Skeptics, Freethinkers, Secular Humanists and the Non-Religious Common Interest," followed by "Kiva Christians," "Team Obama," "Team Europe," and "Australia." The lending teams program substantially increases the amount of funds raised.

There are several directions for future research. A possible next step in this line of research would be to extend this result to other coordination games. While we touch on previous studies of the provision point mechanism, one could attempt to achieve higher contributions to public goods using the same induced identity method used in this study. Our model predicts that successful coordination to higher levels of public goods can be achieved systematically even with a very weak method of increasing other-regarding preferences. Another direction is to evaluate the effects of identity-based teams in the field through natural field experiments in fundraising or online communities.

Appendix A. Proofs

Proof of Proposition 1: Maximizing Equation (6) gives us a new threshold marginal cost value, which is a function of the group-contingent other-regarding parameter α_i^g,

$$c^*(n, \{\alpha_i^g\}_{i=1}^n) = \frac{1}{n - \sum_{i=1}^n \alpha_i^g}. \quad (14)$$

When $\alpha_i^I > \alpha_i^N > \alpha_i^O, \forall i$, the corresponding threshold marginal cost is as follows:

$$c^*(n, \{\alpha_i^I\}_{i=1}^n) > c^*(n, \{\alpha_i^N\}_{i=1}^n) > c^*(n, \{\alpha_i^O\}_{i=1}^n).$$

Furthermore, a more salient group identity increases α_i^I, which leads to an increase in the threshold marginal cost, $c^*(n, \{\alpha_i^I\}_{i=1}^n)$. ∎

Proof of Proposition 3: Based on the standard assumption of the logit model that payoffs are subject to unobserved shocks from a double-exponential distribution, player i's probability density is an exponential function of the expected utility, $u_i^e(x)$,

$$f_i(x) = \frac{\exp(\lambda u_i^e(x))}{\int_{\underline{x}}^{\bar{x}} \exp(\lambda u_i^e(s))ds}, \quad i = 1, \cdots, n, \quad (15)$$

where $\lambda > 0$ is the inverse noise parameter and higher values correspond to less noise.

Let $F_i(x)$ be player i's corresponding effort distribution. For player i, let $G_i(x) \equiv 1 - \prod_{k \neq i}(1 - F_k(x))$ be the distribution of the minimum of the $n-1$ other effort levels. Thus, player i's expected utility from choosing effort level x is:

$$u_i^e(x) = \int_{\underline{x}}^{x} y g_i(y) dy + x(1 - G_i(x)) - c[(1-\alpha_i)x + \alpha_i \int_{\underline{x}}^{\bar{x}} y dF_i(y)], \quad (16)$$

where the first term on the right side is the benefit when another player's effort is below player i's own effort, the second term is the benefit when player i determines the minimum effort, and the last term is the cost of effort weighted by player i's own effort and the average effort of others. The first and very last term of the right side of (16) can be integrated by parts to obtain:

$$u_i^e(x) = \int_{\underline{x}}^{x} \prod_{k \neq i}(1 - F_k(y))dy - c(1-\alpha_i)x + c\alpha_i \int_{\underline{x}}^{\bar{x}} F(y)dy + \underline{x} - c\alpha_i \bar{x}. \quad (17)$$

Differentiating both sides of (15) with respect to x and using the derivative of the expected utility in (17), we obtain:

$$\begin{aligned} f_i'(x) &= \lambda f_i(x) \frac{du_i^e(x)}{dx} \\ &= \lambda f_i(x)[\prod_{k \neq i}(1 - F_k(x)) - c(1-\alpha_i)], \quad i = 1, \cdots n. \quad (18) \end{aligned}$$

Using symmetry (i.e., dropping subscripts), further assuming $\alpha_i = \alpha$ for all i, and integrating both sides of (18), we obtain:

$$\int_{\underline{x}}^{x} f^{'}(s)ds = \lambda \int_{\underline{x}}^{x} f^{'}(s)[1-F(s)]^{n-1}ds - c(1-\alpha)\lambda \int_{\underline{x}}^{x} f(s)ds.$$

Simplifying both sides, we obtain the first-order differential equation for the equilibrium effort distribution:

$$f(x) = f(\underline{x}) + \frac{\lambda}{n}[1-(1-F(x))^n] - c(1-\alpha)\lambda F(x).$$

■

The proofs of Propositions 4 and 5 use similar structure and techniques as those of the corresponding Propositions 4 and 5 in Anderson et al. (2001), with the marginal cost of effort, c, replaced by $c(1-\alpha)$. We present them here for completeness.

Proof of Proposition 4: Let the other regarding parameters be $\alpha_1 < \alpha_2$, and let $F_1(x)$ and $F_2(x)$ denote the corresponding equilibrium effort distributions. We want to show that $F_1(x) > F_2(x)$ for all interior x.

Suppose $F_1(x) = F_2(x)$ on some interval of x values. Then the first two derivatives of these functions must equal on the interval, which violates (18). Therefore, the distribution functions can only be equal, or cross, at isolated points. At any crossing, $F_1(x) = F_2(x) \equiv F$. From (15), the difference in slopes at the crossing is:

$$f_1(x) - f_2(x) = f_1(\underline{x}) - f_2(\underline{x}) - \lambda c(\alpha_2 - \alpha_1)F, \tag{19}$$

which is decreasing in F, and hence is also decreasing in x. It follows that there can be at most two crossings, with the sign of the right-hand side nonnegative at the first crossing and nonpositive at the second. Since the distribution functions cross at $\underline{x}$ and $\bar{x}$, these are the only crossings. The right-hand side of (19) is positive at $x = \underline{x}$ or negative at $x = \bar{x}$, so $F_1(x) > F_2(x)$ for all interior x. This implies that an increase in α results in a distribution of effort that first-degree stochastically dominates that associated with a smaller α. ■

Proof of Proposition 5: First, consider the case $c < c^*$, or $cn(1-\alpha) < 1$. We have to show that $F(x) = 0$ for all $x < \bar{x}$. Suppose not, and $F(x) > 0$ for $x \in (x_a, x_b)$. From (7), we have:

$$\begin{aligned} f(x) &= f(\underline{x}) + \frac{\lambda}{n}[1-(1-F)^n] - c(1-\alpha)\lambda F \\ &= f(\underline{x}) + \frac{\lambda}{n}[1-(1-F)^n - cn(1-\alpha)F] \\ &> \frac{\lambda}{n}[1-(1-F)^n - F] \\ &= \frac{\lambda}{n}(1-F)[1-(1-F)^{n-1}]. \end{aligned}$$

Since density cannot diverge on an interval, $F(\cdot)$ must be zero on any open interval. Therefore, $F(x) = 0$ for $x < \bar{x}$.

Next, consider the case $c < c^*$, or $cn(1-\alpha) > 1$. In this case, we have to prove that $F(x) = 1$ for all $x > 0$. Suppose not, and $F(x) < 1$ for $x \in (x_a, x_b)$. From (7), we have:

$$\begin{aligned} f(\bar{x}) &= f(\underline{x}) + \frac{\lambda}{n}[1 - (1 - F(\bar{x}))^n] - c(1-\alpha)\lambda F(\bar{x}) \\ &= f(\underline{x}) + \frac{\lambda}{n} - c(1-\alpha)\lambda \\ &= f(\underline{x}) + \frac{\lambda}{n}[1 - cn(1-\alpha)], \end{aligned}$$

which enables us to rewrite (7) as:

$$\begin{aligned} f(x) &= f(\bar{x}) - \frac{\lambda}{n}[1 - cn(1-\alpha)] + \frac{\lambda}{n}[1 - (1-F)^n] - c(1-\alpha)\lambda F \\ &= f(\bar{x}) + \frac{\lambda}{n}[cn(1-\alpha)(1-F) - (1-F)^n] \\ &> \frac{\lambda}{n}(1-F)[1 - (1-F)^{n-1}]. \end{aligned}$$

Again, since density cannot diverge on an interval, $F(\cdot)$ must be one on any open interval. Therefore, $F(x) = 1$ for $x > 0$.

Finally, consider the case $c = c^*$, or $cn(1-\alpha) = 1$. In this case, (7) becomes:

$$\begin{aligned} f(x) &= f(\underline{x}) + \frac{\lambda}{n}[1 - (1-F)^n] - c(1-\alpha)\lambda F \\ &= f(\underline{x}) + \frac{\lambda}{n}[1 - (1-F)^n - F] \\ &= f(\underline{x}) + \frac{\lambda}{n}(1-F)[1 - (1-F)^{n-1}]. \end{aligned}$$

This equation implies that the density diverges to infinity as $\lambda \to +\infty$, when $F(x) \neq 0$ or 1. Hence, $F(\cdot)$ jumps from 0 to 1 at the mode M. The above equation implies that $f(\underline{x}) = f(\bar{x})$, so the density is finite at the boundaries and the mode is an interior point. Using symmetry, we can rewrite (18) as $f'(x) = \lambda f(x)[(1-F(x))^{n-1} - c(1-\alpha)] = \lambda f(x)[(1-F(x))^{n-1} - 1/n]$, or $\frac{f'(x)}{\lambda f(x)} = (1-F(x))^{n-1} - 1/n$. Integrating both sides from $\underline{x}$ to $\bar{x}$ yields $\frac{1}{\lambda}\ln(f(\bar{x})/f(\underline{x})) = M - (\bar{x} - \underline{x})/n$, since $1 - F$ equals one to the left of M and zero to the right of M. The left side is zero since $f(\bar{x}) = f(\underline{x})$, so $M = (\bar{x} - \underline{x})/n$. ∎

Appendix B. Experimental Instructions

We present the experimental instructions for the Enhanced Ingroup treatment. Instructions for other treatments are similar and can be found on the second author's website.

Economic Decision Making Experiment: Part 1 Instructions

This is an experiment in decision-making. The amount of money you earn will depend upon the decisions you make and on the decisions other people make. Your earnings are given in tokens. This experiment has 2 parts and 12 participants. Your total earnings will be the sum of your payoffs in each part. At the end of the experiment you will be paid IN CASH based on the exchange rate

$1 = 350 tokens.

In addition, you will be paid $5 for participation. Everyone will be paid in private and you are under no obligation to tell others how much you earn.

Please do not communicate with each other during the experiment unless asked to do so. If you have a question, feel free to raise your hand, and an experimenter will come to help you.

Before the experiment started everyone drew an envelope which contained either a Green or a Red slip. You have been assigned to the Green group if you received a Green slip, and the Red group if you received a Red slip. There are 6 people in each group. Your group assignment will remain the same throughout the experiment. That is, if you drew a Green slip, you will be in the Green group for the rest of the experiment, and if you drew a Red slip, you will be in the Red group for the rest of the experiment.

In Part 1 everyone will be shown 5 pairs of paintings by two artists. You will have 5 minutes to study these paintings. Then you will be asked to answer questions about two other paintings. Each correct answer will bring you 350 additional tokens. You may get help from or help other members in your own group while answering the questions.

After Part 1 has finished, we will give you instructions for the next part of the experiment.

Economic Decision Making Experiment: Part 2 Instructions

The next part of the experiment consists of 50 periods. In each period, you will be randomly matched with 1 other person in the room. If you are a member of the Green group, your match will always be a member of the Green group, and if you are a member of the Red group, your match will always be a member of the Red group. You will be reminded every period of your own group and of your match's group. Your earnings for this part of the experiment depend on your choices as well as the choices of the people you are matched with.

Every period, each person will choose an effort level between 110.00 and 170.00. You will earn a number of tokens equal to the minimum effort level chosen by you and the person you are matched with, minus the cost of your own effort, which is 0.75 times your own effort choice. This is captured by the equation:

Payoff (Tokens) = Minimum Effort - 0.75*Your Effort

Note that the minimum effort here refers to the minimum of the effort levels chosen by you and your match. Refer to the handout for some examples. Note that there may be some case in which you earn a negative payoff. If your final payoff is negative, we will deduct that amount from your participation fee.

We will show you a running tally of the number of tokens you have earned from this part of the experiment, and after 50 rounds, we will add your earnings from Part 1 to this total and convert your total earnings into a dollar amount based on the exchange rate. We will also show you a list of your past effort choices and payoffs, as well as your matches' past effort choices and payoffs.

When you are ready to begin Part 2 of the experiment, please click OK.

Appendix C. Post-Experiment Survey

(*summary statistics in italics*)

Please answer the following survey questions. Your answers will be used for this study only. Individual data will not be exposed.

1. What is your age? (*Mean 21.37, Std Dev 3.27, Median 21, Min 18, Max 40*)
2. What is your gender? (*Male 48.53%, Female 51.47%*)
3. Which of the following best describes your racial or ethnic background? (*Asian 38.73%, Black 6.37%, Caucasian 42.16%, Hispanic 3.43%, Native American 0.49%, Multiracial 4.41%, Other 4.41%*)
4. In what country or region were you primarily raised as a child? (*US/Canada 74.51%, Africa 0.00%, Asia 23.53%, Australia 0.49%, Europe 0.98%, Latin America 0.00%, Middle East 0.49%*)
5. What is your marital status? (*Never Married 96.08%, Currently Married 3.43%, Previously Married 0.49%*)
6. How would you best describe your employment status? (*Employed Full Time 5.88%, Employed Part Time 38.24%, Not Employed 55.88%*)
7. How many siblings do you have? (*Mean 1.55, Std Dev 1.13, Median 1, Min 0, Max 6*)
8. Who in your household is primarily responsible for expenses and budget decisions? Please select all that apply (*Self 38.24%, Spouse 0.49%, Shared Responsibility with Spouse 3.43%, Parent(s) 64.22%, Other 1.47%*)
9. Have you ever voted in a state or federal government election (in any country)? (*Yes 53.92%, No 46.08%*)
10. Before today, how many times have you participated in any economics or psychology experimental studies? (*Mean 3.46, Std Dev 3.47, Median 2, Min 0, Max 20*)
11. In the past twelve months, have you donated money to or done volunteer work for charities or other nonprofit organizations? (*Yes 77.94%, No 22.06 %*)
12. On a scale from 1 to 10, please rate how much you think communicating with your group members helped solve the two extra painting questions, with 1 meaning “not much at all”. (*Mean 6.04, Std Dev 2.90, Median 7, Min 1, Max 10*)
13. On a scale from 1 to 10, please rate how closely attached you felt to your own group throughout the experiment, with 1 meaning “not closely at all”. (*Mean 3.97, Std Dev 2.67, Median 3, Min 1, Max 10*)
14. In Part 2 when you were asked to decide on an effort level, how would you describe the strategies you used? Please select all that apply (*I tried to earn as much money as possible for myself 46.08%, I tried to earn as much money as possible for me and my match 50.00%, I tried to earn more money than my match 17.65%, I gave high effort if my previous matches*

gave high efforts and low effort if my previous matches gave low efforts 27.45%, Other 14.22%)

15. Please tell us how your match's group membership affected your decision. If I had been matched with someone from the other group [my own group], (*I would have picked higher effort levels 16.67% [23.61%], I would have picked lower effort levels 8.33% [1.39%], I would not have changed my effort levels 69.44% [72.22%], Other 5.56% [2.78%]*)

16. On a scale from 1 to 10, please rate how familiar you were with the paintings made by Klee and Kandinsky before this experiment, with 1 meaning "not familiar at all". (*Mean 1.31, Std Dev 1.00, Median 1, Min 1, Max 6*)

Table 1: Features of Experimental Sessions

Treatment		# of Subjects	Group Assignment	Problem Solving
Near-Minimal	Control	3×12	None	None
	Ingroup	3×12	Random	None
	Outgroup	3×12	Random	None
Enhanced	Control	3×12	None	Self
	Ingroup	3×12	Random	Chat
	Outgroup	3×12	Random	Chat

Table 2: Theoretical Distributions

	Effort		
α	μ	σ	Efficiency
-1.0	116.49	5.86	0.563
-0.8	117.40	6.59	0.558
-0.6	118.61	7.50	0.553
-0.4	120.30	8.69	0.546
-0.2	122.79	10.23	0.539
0.0	126.77	12.18	0.533
0.2	133.54	14.21	0.541
0.4	143.37	14.66	0.598
0.6	151.37	12.89	0.684
0.8	156.10	10.83	0.751
1.0	158.99	9.16	0.797

Table 3: Group Identity and Effort Choice: Random-Effect OLS
(Effort = $\beta_0 + \beta_1$*Ingrp+β_2*Outgrp+β_3*Ingrp*Enh+β_4*Outgrp*Enh+β_5*X+u_{it})

Dependent Variable: Effort		
	(1)	(2)
Ingroup	8.82	5.81
	(7.15)	(7.00)
Outgroup	10.76	7.89
	(7.67)	(7.45)
Ingroup*Enhanced	15.38***	15.25***
	(4.57)	(4.51)
Outgroup*Enhanced	-10.41	-10.51
	(11.58)	(11.22)
Female		-3.82*
		(2.06)
Asian		2.44
		(2.55)
Black		-1.91
		(3.29)
Hispanic		1.64
		(4.25)
Married		-3.03
		(7.37)
Employed Full		-0.46
		(3.69)
Employed Part		1.01
		(1.26)
One Sibling		0.13
		(3.34)
Two Siblings		2.66
		(3.31)
Three+ Siblings		6.10*
		(3.48)
Expenses Shared		10.63
		(7.31)
Expenses Parents		-3.71*
		(2.23)
Volunteer		-3.12
		(2.10)
Constant	139.13***	146.78***
	(5.73)	(16.19)
Observations	10800	10200
R^2	0.1691	0.1938

Notes: Standard errors are adjusted for clustering at the session level.
Significant at: * 10% level; *** 1% level.

Table 4: Group Identity and Equilibrium: Probit Regression
(Φ^{-1}(equilibrium) $= \beta_0 + \beta_1$*Ingrp+β_2*Outgrp+β_3*Ingrp*Enh+β_4*Outgrp*Enh+u_{it})

Dependent Variable: Equilibrium	
Ingroup	0.14
	(0.11)
Outgroup	0.02
	(0.11)
Ingroup*Enhanced	0.21**
	(0.10)
Outgroup*Enhanced	0.01
	(0.13)
Observations	5400
Pseudo-R^2	0.0584

Notes: Standard errors are adjusted for clustering at the session level. Significant at: ** 5% level.

Table 5: Average Efficiency by Session and Treatment

	Ingroup	Outgroup	Control
	0.65	0.49	0.57
Near-minimal	0.63	0.67	0.70
	0.70	0.68	0.63
Average	0.66	0.62	0.63
	0.85	0.80	0.58
Enhanced	0.91	0.50	0.80
	0.86	0.55	0.57
Average	0.87	0.62	0.65

Table 6: Group Identity and Efficiency: Random-Effect OLS
(Efficiency = $\beta_0 + \beta_1$*Ingrp+β_2*Outgrp+β_3*Ingrp*Enh+β_4*Outgrp*Enh+u_{it})

Dependent Variable: Efficiency	
Ingroup	0.02
	(0.04)
Outgroup	-0.03
	(0.06)
Ingroup*Enhanced	0.21***
	(0.03)
Outgroup*Enhanced	0.00
	(0.09)
Constant	0.64***
	(0.04)
Observations	5400
R^2	0.1251

Notes: Standard errors are adjusted for clustering at the session level. Significant at: *** 1% level.

Table 7: First-round Effort Distributions across Treatments: Kolmogorov-Smirnov Tests

	Comparison		K-S Statistic	p-value
Near-minimal (NM)	Control	Ingroup	0.17	0.615
	Control	Outgroup	0.31	0.043
	Ingroup	Outgroup	0.19	0.413
Enhanced (E)	Control	Ingroup	0.25	0.150
	Control	Outgroup	0.17	0.615
	Ingroup	Outgroup	0.17	0.615
Combined	NM Ingroup	E Ingroup	0.19	0.413
	NM Outgroup	E Outgroup	0.28	0.083
	NM Control	E Control	0.14	0.825

Table 8: Parameter Calibration of the Stochastic Fictitious Play Model

Treatments	Sessions	Control λ	Control δ	Control α^N	Ingroup λ	Ingroup δ	Ingroup α^I	Outgroup λ	Outgroup δ	Outgroup α^O
Near-minimal	1	0.8	0.7	0.27	5.4	0.8	0.51	0.1	0.4	0.07
	2	4.7	1.0	0.17	0.4	0.5	0.34	2.2	0.7	0.93
	3	1.6	0.6	0.75	2.2	0.7	1.00	2.9	0.8	0.78
	Average	2.4	0.8	0.40	2.7	0.7	0.62	1.7	0.6	0.59
Enhanced	1	1.2	0.7	0.12	2.2	0.7	1.00	2.4	1.0	1.00
	2	2.5	0.7	1.00	3.0	0.7	1.00	0.8	0.3	-0.22
	3	1.7	0.5	-0.16	2.9	0.3	0.91	0.6	0.7	0.24
	Average	1.8	0.6	0.32	2.7	0.6	0.97	1.3	0.7	0.34

Note: λ, δ and α^g are the sensitivity, discount, and other-regarding parameters, respectively.

Table 9: Kolmogorov-Smirnov Tests of Equality of Distributions Between Simulations and Choices in the Last Five Rounds

Treatments	Near-Minimal			Enhanced		
Period	Control	Ingroup	Outgroup	Control	Ingroup	Outgroup
46	0.1440	0.1607	0.1889	0.1060	0.1500	0.1857
47	0.1893	0.1996*	0.1746	0.1048	0.1647	0.1750
48	0.1567	0.1583	0.1675	0.0940	0.1456	0.2405**
49	0.1492	0.1611	0.1635	0.0889	0.1718	0.2393**
50	0.1948*	0.1603	0.2060*	0.1393	0.1635	0.2607***

Note: Significant at: * 10% level; ** 5% level; *** 1% level.

Table 10: Effort Distributions in the Last Five Rounds

Treatment		Calibrated α^g	Predicted Mean	Predicted SD	Actual Mean	Actual SD
Near-Minimal	Control	0.40	143.37	14.66	133.28	13.07
	Ingroup	0.62	151.97	12.68	148.29	19.18
	Outgroup	0.59	151.06	13.00	157.46	20.96
Enhanced	Control	0.32	139.32	14.82	132.83	27.13
	Ingroup	0.97	158.63	9.38	166.15	6.78
	Outgroup	0.34	140.34	14.82	133.65	25.97

Table 11: Summary of Studies Regarding the Minimum Effort Game

	Study	Treatment	Efforts	T (# of rounds)	n (# per match)	$\pi_i = a\min(x) - cx_i + b$ / $P = a\min(x) - c\sum_i x_i$: a	b	c	Threshold $c^* = \frac{a}{n}$	Theoretical Prediction	Observed Trend
Baseline	Van Huyck, Battalio, Beil (1990)	Large Groups	{1,...,7}	10	14-16	0.20	0.60	0.10	0.01	Low	Low
		No Cost	{1,...,7}	5	14-16	0.20	0.60	0.00	0.01	High	High
		2-person	{1,...,7}	7	2	0.20	0.60	0.10	0.10	High	High
	Goeree, Holt (2005)	2-person, c=1/4	[110,170]	10	2	1.00	0.00	0.25	0.50	High	High
		2-person, c=3/4	[110,170]	10	2	1.00	0.00	0.75	0.50	Low	Low
		3-person, c=1/10	[110,170]	10	3	1.00	0.00	0.10	0.33	High	High
	Knez, Camerer (1994)	3-person	{1,...,7}	5	3	0.20	0.60	0.10	0.07	Low	Low
		6-person	{1,...,7}	5	6	0.20	0.60	0.10	0.03	Low	Low
Transfer of Precedent	Camerer, Knez (2000)	2-person	{1,...,7}	5	2	0.20	0.60	0.10	0.10	High	High
		2-person	{1,...,7}	5	2	0.20	0.60	0.10	0.10	High	High
		3-person	{1,...,7}	5	3	0.20	0.60	0.10	0.07	Low	Low
		2-, 3-person	{1,...,7}	5	2→3	0.20	0.60	0.10	0.07	**Low**	**High**
	Weber (2006)	No Growth	{1,...,7}	12	12	0.20	0.20	0.10	0.02	Low	Low
		No History	{1,...,7}	22	2→12	0.20	0.20	0.10	0.02	Low	Low
		Fast Growth	{1,...,7}	22	2→12	0.20	0.20	0.10	0.02	Low	Low
		Slow Growth	{1,...,7}	22	2→12	0.20	0.20	0.10	0.02	**Low**	**High**
Inter-Group Competition	Bornstein, Gneezy Nagel (2002)	No Comp.	{1,...,7}	10	7	20	60	10	2.86	Low	Low
		Info	{1,...,7}	10	7	20	60	10	2.86	Low	Low
		Group Comp.	{1,...,7}	10	7	20	60	10	2.86	**Low**	**High**
Communication	Chaudhuri, Schotter, Soper (2001)	Low Cost	{1,...,7}	10	8	0.20	0.60	0.10	0.03	Low	Low
		Progenitor	{1,...,7}	10	8	0.20	0.60	0.10	0.03	Low	Low
		History, Advice	{1,...,7}	10	8	0.20	0.60	0.10	0.03	Low	Low
		Advice	{1,...,7}	10	8	0.20	0.60	0.10	0.03	Low	Low
		Public Advice	{1,...,7}	10	8	0.20	0.60	0.10	0.03	**Low**	**High**
	Brandt, Cooper (2007)	Computer	{0,...,40}	20	4	10	200	5	2.50	**Low**	**High**
		No Comm.	{0,...,40}	20	4	9.3*	200	5	2.33	Low	Low
		One-way Comm.	{0,...,40}	20	4	9.3*	200	5	2.33	**Low**	**High**
		Two-way Comm.	{0,...,40}	20	4	9.9*	200	5	2.48	**Low**	**High**

*Chosen by subjects; average reported

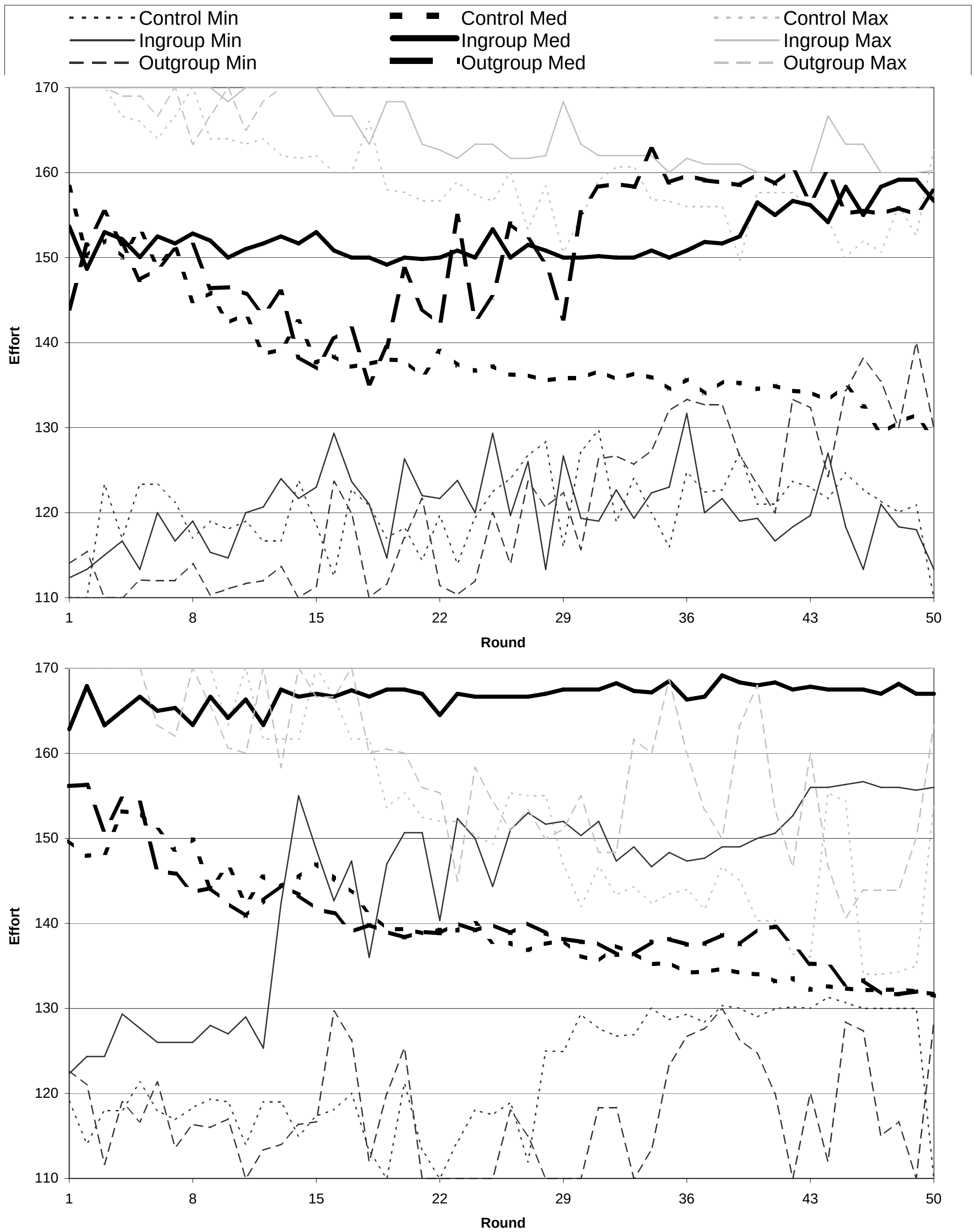

Figure 1: Effort Level in the Near-Minimal (Top) and Enhanced (Bottom) Treatments

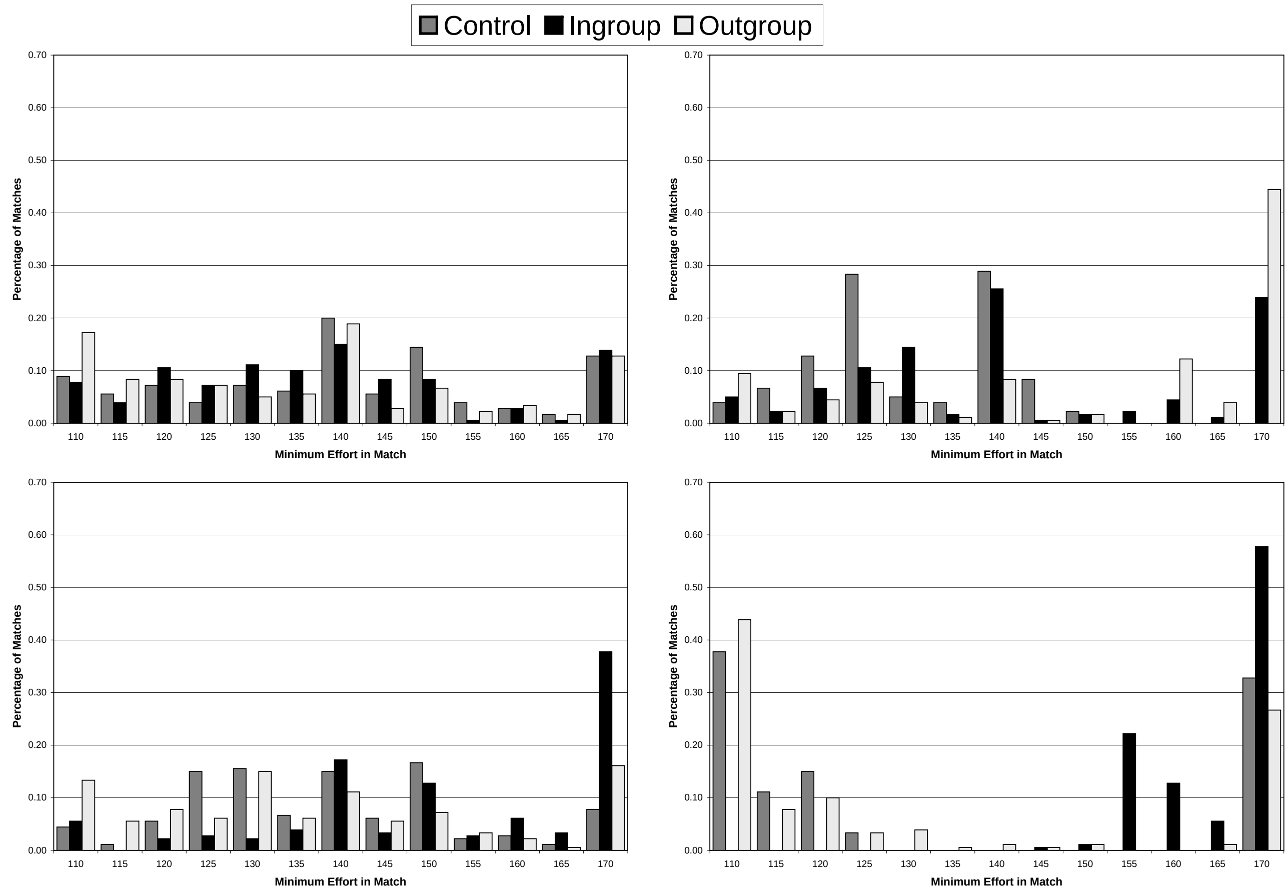

Figure 2: Minimum Effort Level in each Match for the First 10 Periods (Left Column) and the Last 10 Periods (Right Column), Separated by Near-Minimal (Top) and Enhanced (Bottom) Sessions

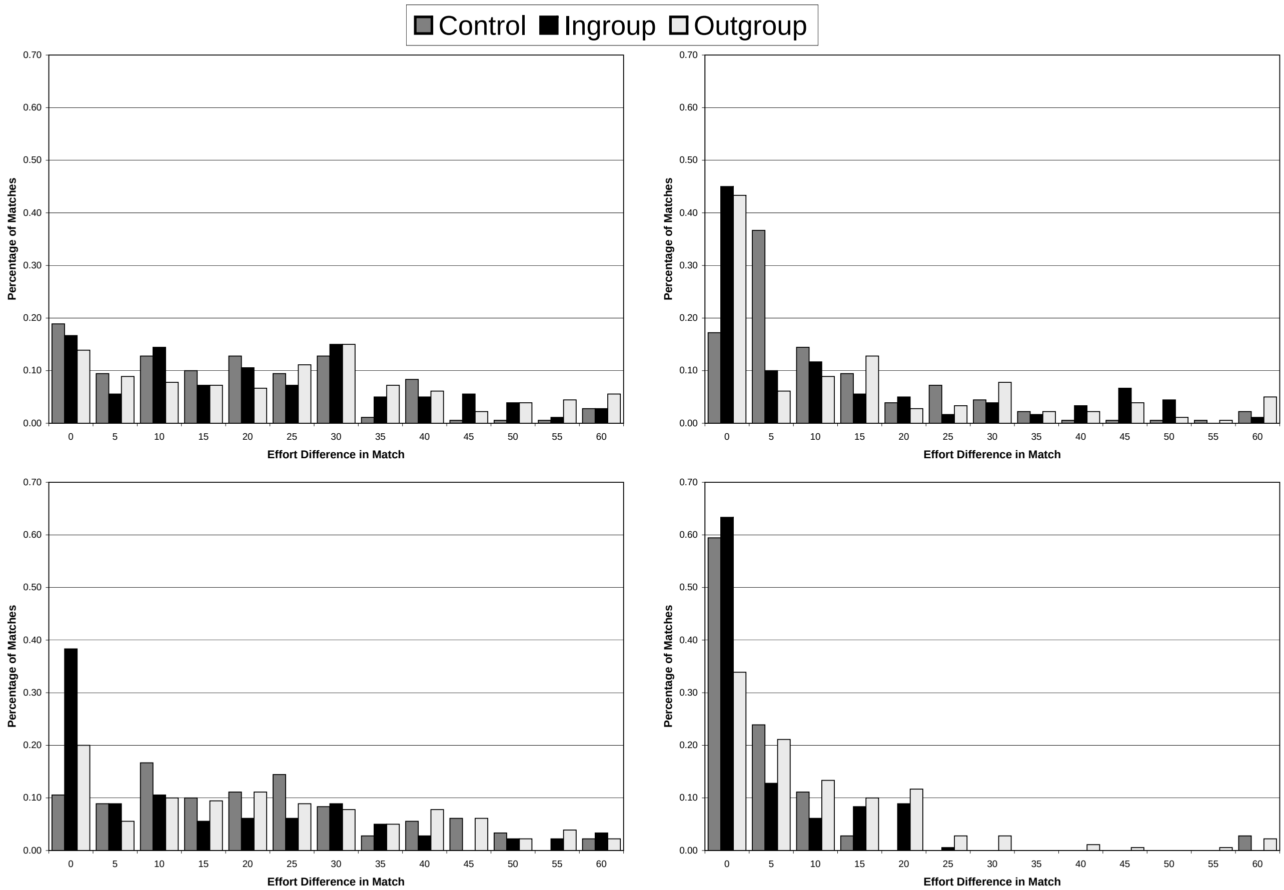

Figure 3: Wasted Effort in each Match for the First 10 Periods (Left Column) and the Last 10 Periods (Right Column), Separated by Near-Minimal (Top) and Enhanced (Bottom) Sessions

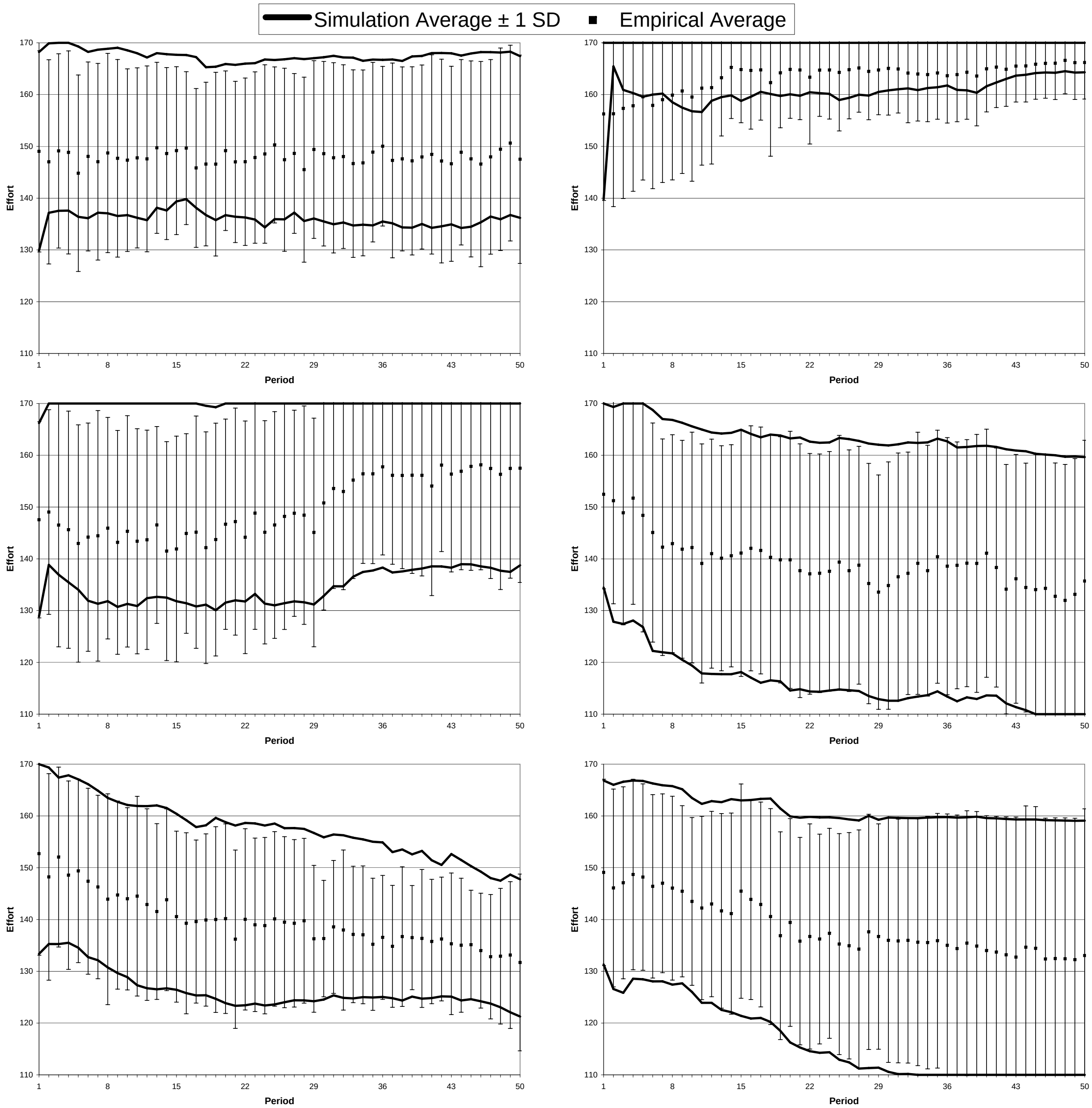

Figure 4: Simulation of Stochastic Fictitious Play (Borders) and Data (Black Dots and Error Bars) in the Ingroup (Row 1), Outgroup (Row 2), and Control (Row 3) Sessions, separated by Near-Minimal (Left Column) and Enhanced (Right Column) Sessions

References

Akerlof, George A., "The Missing Motivation in Macroeconomics," *American Economic Review*, March 2007, *97* (1), 5–36.

__ **and Rachel E. Kranton**, "Economics and Identity," *Quarterly Journal of Economics*, August 2000, *115* (3), 715–753.

__ **and** __ , "Identity and Schooling: Some Lessons for the Economics of Education," *Journal of Economic Literature*, December 2002, *40* (4), 1167–1201.

__ **and** __ , "Identity and the Economics of Organizations," *Journal of Economic Perspective*, Winter 2005, *19* (1), 9–32.

Alesina, Alberto and Eliana La Ferrara, "Ethnic Diversity and Economic Performance," *Journal of Economic Literature*, September 2005, *43*, 721–761.

Anderson, Simon P., Jacob K. Goeree, and Charles A. Holt, "Minimum-Effort Coordination Games: Stochastic Potential and Logit Equilibrium," *Games and Economic Behavior*, 2001, *34* (2), 177 – 199.

Bagnoli, Mark E. and Bart L. Lipman, "Provision of Public Goods: Fully Implementing the Core Through Private Contributions," *Review of Economic Studies*, October 1989, *56* (4), 583–601.

__ **and Michael McKee**, "Voluntary Contribution Games: Efficient Private Provision of Public Goods," *Econ. Inquiry*, April 1991, *29*, 351–366.

Ball, J R, "'Space missions' Focus on Team Building," *The Greater Baton Rouge Business Report*, March 1999, *17* (15), 31.

Basu, Kaushik, "Identity, Trust and Altruism: Sociological Clues to Economic Development," 2006. CAE Working Paper #06-06.

Benabou, Roland and Jean Tirole, "Identity, Dignity and Taboos: Beliefs as Assets," 2007. CEPR Discussion Paper 6123.

Blume, Lawrence E., "The Statistical Mechanics of Strategic Interaction," *Games and Economic Behavior*, 1993, *5* (3), 387 – 424.

Bolton, Gary E. and Axel Ockenfels, "ERC: A Theory of Equity, Reciprocity, and Competition," *American Economic Review*, March 2000, *90* (1), 166–193.

Bornstein, Gary, Uri Gneezy, and Rosmarie Nagel, "The Effect of Intergroup Competition on Group Coordination: An Experimental Study," *Games and Economic Behavior*, October 2002, *41*, 1 – 25.

Brandts, Jordi and David J. Cooper, "It's What You Say, Not What You Pay: An Experimental Study of Manager-Employee Relationships in Overcoming Coordination Failure," *Journal of the European Economic Association*, 2007, *5* (6), 1223–1268.

Brewer, Marilynn B., "The Psychology of Prejudice: Ingroup Love and Outgroup Hate?," *Journal of Social Issues*, 1999, *55* (3), 429–444.

Camerer, Colin F., *Behavioral Game Theory: Experiments on Strategic Interactions*, Princeton: Princeton University Press, 2003.

__ **and Ulrike Malmendier**, "Behavioral Organizational Economics," in Peter Diamond and Hannu Vartiainen, eds., *Behavioral Economics and Its Applications*, Princeton and Oxford: Princeton University Press, 2007.

Charness, Gary and Matthew Rabin, "Understanding Social Preferences with Simple Tests," *Quarterly Journal of Economics*, August 2002, *117* (3), 817–869.

__ **, Luca Rigotti, and Aldo Rustichini**, "Individual behavior and group membership," *American*

Economic Review, September 2007, *97*, 1340 – 1352.
Chaudhuri, Ananish, Andrew Schotter, and Barry Sopher, "Talking Ourselves to Efficiency: Coordination in Inter-Generational Minimum Effort Games with Private, Almost Common and Common Knowledge of Advice," *The Economic Journal*, 2009, *119* (534), 91–122.
Chen, Yan, "Incentive-Compatible Mechanisms for Pure Public Goods: A Survey of Experimental Research," in Charles Plott and Vernon Smith, eds., *The Handbook of Experimental Economics Results*, Vol. 1, Amsterdam: North-Holland, 2008, pp. 625 – 643.
__ **and Sherry Xin Li**, "A CES Model of Group Identity and Social Preferences," 2008. Unpublished Manuscript.
__ **and** __ , "Group Identity and Social Preferences," *American Economic Review*, March 2009, *99* (1), 431–457.
Cheung, Yin-Wong and Daniel Friedman, "Individual Learning in Normal Form Games: Some Laboratory Results," *Games and Economic Behavior*, 1997, *19* (1), 46–76.
Cooper, Russell W., Douglas DeJong, Robert Forsythe, and Thomas Ross, "Communication in the Battle of the Sexes: Some Experimental Results," *Rand Journal of Economics*, 1989, *20*, 568–587.
Cox, James C., Daniel Friedman, and Steven Gjerstad, "A Tractable Model of Reciprocity and Fairness," *Games and Economic Behavior*, April 2007, *59* (1), 17–45.
Crawford, Vincent and Bruno Broseta, "What Price Coordination? The Efficiency-Enhancing Effect of Auctioning the Right to Play," *The American Economic Review*, 1998, *88* (1), 198–225.
Crawford, Vincent P., "An 'evolutionary' Interpretation of Van Huyck, Battalio, and Beil's Experimental Results on Coordination," *Games and Economic Behavior*, 1991, *3* (1), 25 – 59.
__ , "Adaptive Dynamics in Coordination Games," *Econometrica*, 1995, *63* (1), 103–143.
Croson, Rachel T. A., Melanie B. Marks, and Jessica Snyder, "Groups Work for Women: Gender and Group Identity in the Provision of Public Goods," *Negotiation Journal*, October 2008, *24* (4), 411–427.
Eckel, Catherine C. and Philip J. Grossman, "Managing Diversity by Creating Team Identity," *Journal of Economic Behavior & Organization*, November 2005, *58* (3), 371–392.
Falk, Armin and Urs Fischbacher, "A Theory of Reciprocity," *Games and Economic Behavior*, February 2006, *54* (2), 293–315.
Fehr, Ernst and Klaus M. Schmidt, "The Theory of Fairness, Competition, and Cooperation," *Quarterly Journal of Economics*, August 1999, *114* (3), 817–868.
Fischbacher, Urs, "z-Tree: Zurich Toolbox for Ready-made Economic Experiments," *Experimental Economics*, 2007, *10* (2), 171–178.
Fudenberg, Drew and David Levine, *The theory of learning in games*, Vol. 2 of MIT Press Series on Economic Learning and Social Evolution, Cambridge, MA: MIT Press, 1998.
Goeree, Jacob K. and Charles A. Holt, "An Experimental Study of Costly Coordination," *Games and Economic Behavior*, 2005, *51* (2), 349 – 364. Special Issue in Honor of Richard D. McKelvey.
Horswill, Amanda, "Putting Mateship to Work," *The Courier Mail*, October 2007.
Knez, Marc and Colin Camerer, "Creating Expectational Assets in the Laboratory: Coordination in 'Weakest- Link' Games," *Strategic Management Journal*, 1994, *15*, 101–119.
__ **and** __ , "Increasing Cooperation in Prisoner's Dilemmas by Establishing a Precedent of Efficiency in Coordination," *Organizational Behavior and Human Decision Processes*, 2000, *82*, 194–216.

Levine, David K., "Modeling Altruism and Spitefulness in Experiments," *Review of Economic Dynamics*, July 1998, *1* (3), 593–622.

McDermott, Rose, "Psychological Approaches to Identity: Definitions, Measurement and Experimentation," in R. Abdelal, Y. Herrera, A. I. Johnson, and Rose McDermott, eds., *Measuring Identity: A Guide for Social Science Research*, Cambridge, U.K.: Cambridge University Press, forthcoming.

McKelvey, Richard D. and Thomas R. Palfrey, "Quantal Response Equilibria for Normal Form Games," *Games and Economic Behavior*, 1995, *10*, 6–38.

McLeish, Kendra N. and Robert J. Oxoby, "Identity, Cooperation, and Punishment," 2007. IZA Discussion Paper No. 2572.

Menezes, Flavio M., Paulo K. Monteiro, and Akram Temimi, "Private provision of discrete public goods with incomplete information," *Journal of Mathematical Economics*, 2001, *35* (4), 493 – 514.

Monderer, Dov and Lloyd S. Shapley, "Potential Games," *Games and Economic Behavior*, 1996, *14*, 124–143.

Mysker, Michael B., Peter K. Olson, and Arlington Williams, "The Voluntary Provision of a Threshold Public Good: Further Experimental Results," in R. Mark Isaac, ed., *Research in Experimental Economics*, Vol. 6, Greenwich, CT: JAI Press, 1996, pp. 149–163.

Ochs, Jack, "Coordination Problems," in John Kagel and Alvin Roth, eds., *Handbook of Experimental Economics*, Princeton, New Jersey: Princeton University Press, 1995, pp. 195 – 251.

Rabin, Matthew, "Incorporating Fairness into Game Theory and Economics," *American Economic Review*, December 1993, *83* (5), 1281–1302.

Selten, Reinhard, "Axiomatic characterization of the quadratic scoring rule," *Experimental Economics*, June 1998, *1* (1), 43–62.

Shih, Margaret, Todd L. Pittinsky, and Nalini Ambady, "Stereotype Susceptibility: Identity Salience and Shifts in Quantitative Performance," *Psychological Science*, 1999, *10* (1), 81–84.

Tajfel, Henri and John Turner, "The Social Identity Theory of Intergroup Behavior," in Stephen Worchel and William Austin, eds., *The Social Psychology of Intergroup Relations*, Chicago: Nelson- Hall, 1986.

__ , Michael Billig, R. Bundy, and Claude L. Flament, "Social Categorization and Inter-Group Behavior," *European Journal of Social Psychology*, 1971, *1*, 149–177.

Van Huyck, John B., Raymond C. Battalio, and Richard O. Beil, "Tacit Coordination Games, Strategic Uncertainty, and Coordination Failure," *American Economic Review*, 1990, *80*, 234–248.

Weber, Roberto A., "Managing growth to achieve efficient coordination in large groups," *American Economic Review*, 2006, *96* (1), 114 – 126.