The Potential of Social Identity for Equilibrium Selection

By Roy Chen AND Yan Chen[*]

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. 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. For those with a salient group identity, consistent with our theory, we find that learning leads to ingroup coordination to the efficient high-effort equilibrium. Additionally, our theoretical framework reconciles findings from a number of coordination game experiments. JEL: C7, C91

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. 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. To create a common identity

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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, 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), contract theory (Akerlof and Kranton 2005), economic development (Basu 2006), and public goods provision (e.g., Croson, Marks and Snyder (2008), Eckel and Grossman (2005)), summarized in Akerlof and Kranton (2010).

In this paper, we systematically induce groups and social preferences in the laboratory, and associate this experimental manipulation with forming group identities. We model social identity as 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. 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 the Sexes (Charness, Rigotti and Rustichini 2007). Our theoretical model provides a unifying framework for understanding these experimental results (Appendix F).

The rest of the paper is organized as follows. Section I reviews the main experimental and theoretical results on minimum-effort games. In Section II, we present the theory of potential games, incorporate social identity into the potential function, and derive theoretical predictions. In Section III, we present our experimental design. Section IV presents our hypotheses. Section V presents the analysis and results. Section VI concludes.

I The Minimum-Effort Coordination Game

The minimum-effort game is one the most well known coordination games. Rather than exhaustively reviewing the large experimental economics literature on coordination games,[1] 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 Appendix F.

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

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

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 can 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-

[1] We refer the reader to chapter 7 of Camerer (2003) for an overview of the literature.

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,[2] and that the empirical regularities from VHBB are consistent with 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.,

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

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 III, follows Goeree and Holt's, with the addition of induced group identities to test the effect of group identity on equilibrium selection.

II Potential Games

Both theoretical and experimental studies of coordination games point to the importance of learning dynamics in equilibrium selection. 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

[2]We introduce potential games in Section II

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:

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

A potential function is a global function defined on the space of pure strategy profiles such that the change in any player's payoffs from a unilateral deviation is exactly matched by the change in the potential P. To determine whether a game has a potential function, Ui (2000) notes that every potential game has a symmetric structure. The Cournot oligopoly game with a linear inverse demand function is a well-known example of a potential game, where each player's payoff depends on a symmetric market aggregate of all players' outputs (the inverse demand function), and also on her own output (the cost of production). Similarly, the minimum-effort game defined by Equation (1) has a symmetric interaction term, $a \cdot \min\{x_1, \ldots, x_n\}$, and a term depending only on a player's own strategy, $c \cdot x_i$.

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.,

$$\text{(4)} \qquad \frac{\partial^2 \pi_i(x_i, x_{-i})}{\partial x_i \partial x_j} = \frac{\partial^2 \pi_j(x_j, x_{-j})}{\partial x_i \partial x_j} = \frac{\partial^2 P(x_i, x_{-i})}{\partial x_i \partial x_j}, \quad \forall i, j \in N.$$

Equation (4) can be used to identify potential games. If (4) holds, the potential function P can be calculated by integrating (4). Similar conditions hold for non-differentiable payoff functions by replacing "differentials" with "differences" (Monderer and Shapley 1996).

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:

$$\text{(5)} \qquad P(x_1, \ldots, x_n) = a \cdot \min\{x_1, \ldots, x_n\} - c \sum_{i=1}^{n} x_i.$$

In most previous experiments using the minimum-effort game, subjects converge or begin to converge towards the equilibrium that maximizes the potential function.[3] 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 $14 \leq n \leq 16$, 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 players' group membership are ingroup, outgroup or group-neutral.

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 payoff of the other players,[4]

$$(6) \quad u_i(x) = \alpha_i^g \cdot \bar{\pi}_{-i} + (1 - \alpha_i^g) \cdot \pi_i(x) = \min\{x_1, \cdots, x_n\} - c \cdot [\alpha_i^g \cdot \bar{x}_{-i} + (1 - \alpha_i^g) \cdot x_i],$$

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 (6) is a potential game, which admits the following potential function,

$$(7) \qquad P(x_1, \cdots, x_n) = \min\{x_1, \cdots, x_n\} - c \sum_{i=1}^{n} (1 - \alpha_i^g) x_i.$$

[3]Exceptions, such as Bornstein et al. (2002), use intergroup competition to promote higher effort levels, which is consistent with our theoretical framework (Appendix F).

[4]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. See Sobel (2005) for a review of these models. Chen and Li (2009) extend the linear model of Charness and Rabin (2002) to incorporate social identity. We use a linear model here for simplicity.

Note that the Nash equilibria for the transformed game defined by (6) 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. In what follows, ingroup (outgroup) matching refers to the treatment when only members of the same group (different groups) play the minimum-effort game with each other. 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^*.*

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., $c > c^*(n, \{\alpha_i^N\}_{i=1}^n)$, so that play converges to the low-effort equilibrium, and investigate whether induced group identity can lead to convergence to the high-effort equilibrium.

As experimental data are often noisy and better explained by statistical equilibrium concepts, 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 (6). 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:*

$$f(x) = f(\underline{x}) + \frac{\lambda}{n}[1 - (1 - F(x))^n] - c(1 - \alpha)\lambda F(x). \tag{8}$$

Equation (8) plays a key role in both our comparative statics results and our data analysis. We compute the logit equilibrium effort distribution in Section III as a benchmark for the final-rounds analysis in Section V. 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 (8), 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).*

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 the distribution under group-neutral matching, which, in turn, first-order stochastically dominates the distribution 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 $c^* = 1/[n(1-\alpha)]$.*

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

III Experimental Design

We design our experiments to determine the effects of group identity on equilibrium selection, to test the comparative statics results from Section II, and to investigate the interactions of group identity and learning. In our experiments, we focus on two-person matches in the minimum-effort game. We now present the economic environments and our experimental procedure.

A 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: $\pi_i(x_i, x_j) = \min\{x_i, x_j\} - 0.75 \cdot x_i$, 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 (5), 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 $P(x_i, x_j) = \min\{x_i, x_j\} - 0.75 \cdot [(1-\alpha_i^g)x_i + (1-\alpha_j^g)x_j]$, where α_i^g is the weight that subject i 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.

B 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 and enhanced treatments. Our near-minimal 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.

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, including ours, since subjects' monetary payoffs are usually tied to their choices. Since this criterion is not met, we refer to these treatments as *near minimal*.

Our enhanced treatment is designed to increase the salience of group identity by incorporating a group problem-solving stage, where salience refers to the relative importance or prominence of group membership. In our model, salience can be captured by the group-contingent other-regarding parameter, $\alpha_i^I - \alpha_i^N$, i.e., the difference between how altruistic player i feels towards an ingroup match when group identity is induced or primed relative to when it is not induced, such as in the control condition.[5] To implement the enhanced treatment, after being randomly assigned to groups, subjects are asked to solve a problem about a pair of paintings. They can use an online communication 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 communication program.

Our experimental process is summarized as follows:

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 and are

[5] Alternative formulations of salience, e.g., the difference of group-contingent altruism parameters between ingroup and outgroup members, $\alpha_i^I - \alpha_i^O$, are not quite as general. Our formulation can incorporate situations where one dimension of own group identity is primed without necessarily activating an outgroup, such as in Shih et al. (1999).

[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.

[7] The five pairs of paintings are: 1A *Gebirgsbildung*, 1924, by Klee; 1B *Subdued Glow*, 1928, by Kandinsky; 2A

told that each of them was painted by either Klee or Kandinsky, and that they both could have been painted by the same artist. 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 communication 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 communication option. For each correct answer, a subject earns 350 tokens (the equivalent of $1), though she is not told what the correct responses are until the end of the experiment, after the minimum-effort game has been played. 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.[9]

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

Past experimental research finds that the extent to which induced identity affects behavior depends on the salience of the social identity. For example, Eckel and Grossman (2005) use induced

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]This matching protocol introduces a potential confound, as subjects interact with 5 other (ingroup), or 6 other (outgroup), or 11 other (control) players. It is possible that interacting with a smaller number of players could increase the weight on one's match. In particular, this could be a reason for the lack of difference in effort levels between the outgroup and control sessions in both treatments. We thank an anonymous referee for pointing this out.

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). Based on previous findings, we expect that group effects will be stronger in our enhanced treatments than our near-minimal treatments.

Table 1: Features of Experimental Sessions

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

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, 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.

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

IV 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:* $\bar{x}^{EO} < \bar{x}^{MO}$.

We would also like to examine which aspects of the problem-solving stage have an effect on effort. We do this by examining the communication logs from the problem-solving stage. We identify components of these communications and examine how they affect effort. Our belief is that subjects who contribute more to the communication process feel more closely connected to their groups, and therefore have a higher value of α^I and a lower value of α^O.

HYPOTHESIS 6 (Effect of Communication on Effort Choices: Ingroup)**.** *The average effort level in the enhanced ingroup treatment is higher when a subject submits more lines, is more engaged, and gives more analysis during the problem-solving stage.*

HYPOTHESIS 7 (Effect of Communication on Effort Choices: Outgroup)**.** *The average effort level in the enhanced outgroup treatment is lower when a subject submits more lines, is more engaged, and gives more analysis during the problem-solving stage.*

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

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

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. As theoretical benchmarks, we use the equilibrium distribution described in Equation (8) to compute the expected effort and efficiency for different values of α. These computation results are included in Appendix A.

V 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.

A Group Identity and Effort

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

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 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 seems to increase the effort level in the near-minimal treatments, but the effects are not as strong. We next use random-effects regressions to investigate the significance of the observed patterns.

In Table 2, we present two random-effects 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

[11] Using 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).

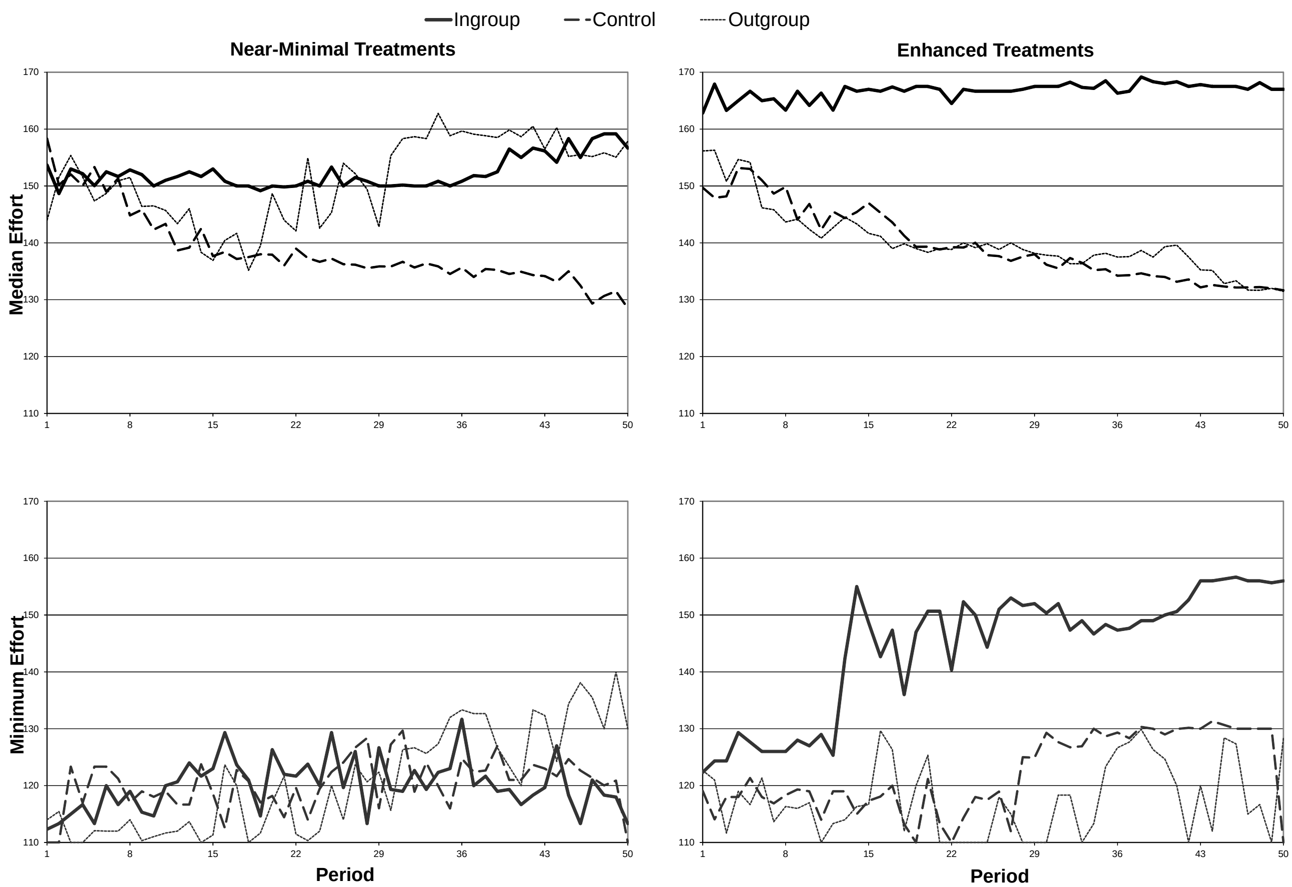

Figure 1: Median (Top Row) and Minimum (Bottom Row) Effort in the Near-Minimal (Left Column) and Enhanced (Right Column) Treatments

Table 2: Group Identity and Effort Choice: Random-Effects

(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)
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.

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 2, we omit some demographic variables, but none that are significant. We summarize the results from Table 2 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 2, 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. The lack of outgroup discrimination in our experimental setup is not surprising, as the outgroup and control sessions do not differ except for the categorization of groups, whereas in other environments negative behavior towards outsiders can and do happen (Deaux 1996).

In several social identity experiments, such as Eckel and Grossman (2005) and Charness et al. (2007), identity salience is crucial in changing behavior. We observe a similar effect in our experiment.

Result 3 (Effect of group salience on effort)**.** *When groups are more salient, participants in the ingroup sessions choose significantly higher effort levels.*

Support. *In Table 2, 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 solve a problem 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 C, we estimate the parameter α_i^g together with other parameters of the adaptive learning model described previously.

We next investigate the factors in the problem-solving stage that affect the amount of effort given in the minimum-effort game. We concentrate on the enhanced sessions, which included 3 control, 3 ingroup, and 3 outgroup sessions. In the control sessions, the subjects guessed the artists by themselves. In the ingroup and outgroup sessions, the subjects were allowed to communicate with other members of their own group via the chat feature in z-Tree (Fischbacher 2007).

In order to examine the components of communication, we take the communication logs and code them. Our coding procedures follow the standard practice in content analysis (Krippendorff 2003). There are 6 sessions with communication, with 2 sets of logs for each session. We have 4 independent coders read through each communication log and identify various aspects of the communication. These coders are asked to examine the communication logs on 3 different levels: the line level, the subject level, and the group level. Details of the coding procedure and instructions can be found in Appendix D.

Among the enhanced sessions, we include these coded variables and other variables in a random-effects regression. First, we examine the inter-rater reliability for each coding category. The interclass correlation (ICC) value for each category is displayed in Table 6 in Appendix E. As is standard when examining coded communication logs, we drop all variables that do not have an ICC of at least 2/3. This means that we only keep the painting analysis (whether a line shows painting analysis), question (whether a line is a question about the paintings), and (group-level) agreement variables, as well as the subject engagement variable. For these variables, we include in the regression the number of times a subject had a line that was coded in the respective category by 3 out of 4 of the coders.

We also include each subject's line count, painting responses, and demographics in the random-effects regression. The line count is simply the number of times a subject clicks "submit" during the communication process. This variable is a measure of a subject's level of contribution to the communication, since speaking more during this process helps everyone else in the group and costs the speaker a small amount of effort. The painting responses are dummy variables, one for each of paintings 6 and 7, indicating whether that subject correctly identified the paintings' artists. So, a subject received a 1 for the painting 6 (7) dummy variable if that subject submitted the answer "Klee" ("Kandinsky") for painting 6 (7) and a 0 otherwise. While we expect the line count to have some effect on the amount of contributed effort, we do not expect the painting variables to have an effect since the subjects are not told who the actual painters are for paintings 6 and 7 until after the minimum-effort game is played. Finally, we include the same demographics that were included in the original regressions.

Result 4 (Effect of communication on effort)**.** *Subjects give more effort to ingroup members in the minimum-effort game if they ask more questions during the problem-solving stage.*

Support. *In Table 3, the coefficient on the Ingroup*Questions variable is significant ($p = 0.020$), while the coefficient on the Outgroup*Questions variable is marginally significant ($p = 0.079$). The coefficients for the other coded variables, the line count, and the painting responses are not significant.* ∎

Table 3 shows the results of the regression, not including the demographic variables. Result 4 shows that only the act of asking questions during the communication stage has any significant effect on effort. When a subject asks more questions to members of her own group, she gives more to members of her own group and less to members of the other group. This result refutes both Hypotheses 6 and 7. Also, as predicted, answering the painting problems correctly does not affect the amount of effort given later in the experiment. Even though subjects perform better in the problem-solving task after having communicated with their group members[12], this does not affect the amount of effort they give in the minimum-effort game. Result 4 suggests that an increase in

[12]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).

group salience takes place during the communication stage, seemingly through generalized reciprocity (Yamagishi and Kiyonari 2000). When a subject asks a question regarding the paintings, it is answered by another subject 94% of the time. By asking more questions and therefore receiving more help from their group members, subjects seem to feel obligated to give more effort to their group members in the minimum-effort game.

B Equilibrium Play and Efficiency

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 "wasted" efforts exhibited by each match for the first 10 (left column) and last 10 (right column) periods in each session. The top rows show the near-minimal treatments while the bottom rows show the enhanced treatments. 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 2, matches with no wasted effort indicate subjects are in a Nash equilibrium.

Several results can be observed from this figure. 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 the amount of wasted effort. Furthermore, wasted effort seems to be uniformly distributed among the allowed values. In the enhanced treatments, the first 10 periods show that there is a much higher frequency of little to no waste in enhanced ingroup sessions, 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. Furthermore, the frequency of no waste is higher in the enhanced than the near-minimal treatments.

We now use a probit regression to investigate the significance of the observed patterns. In Table 7 in Appendix E, we present the results of this regression, reporting the marginal effects.

Table 3: Communication Characteristics and Effort Choice: Random-Effect Model

	Dependent Variable: Effort
Ingroup	33.90***
	(11.608)
Outgroup	-0.19
	(11.388)
Lines	0.37
	(0.645)
Painting 6 Correct	-1.74
	(5.606)
Painting 7 Correct	-0.32
	(8.396)
Ingroup*Analysis	-0.5
	(0.509)
Outgroup*Analysis	-0.19
	(1.091)
Ingroup*Question	3.56**
	(1.528)
Outgroup*Question	-4.02*
	(2.287)
Ingroup*Agreement	0.06
	(1.415)
Outgroup*Agreement	1.51
	(1.692)
Ingroup*Engagement	-4.41
	(4.032)
Outgroup*Engagement	0.33
	(4.532)
Constant	139.84***
	(13.441)
Observations	5400
R^2	0.3549

Notes: Standard errors are adjusted for clustering at the session level.

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

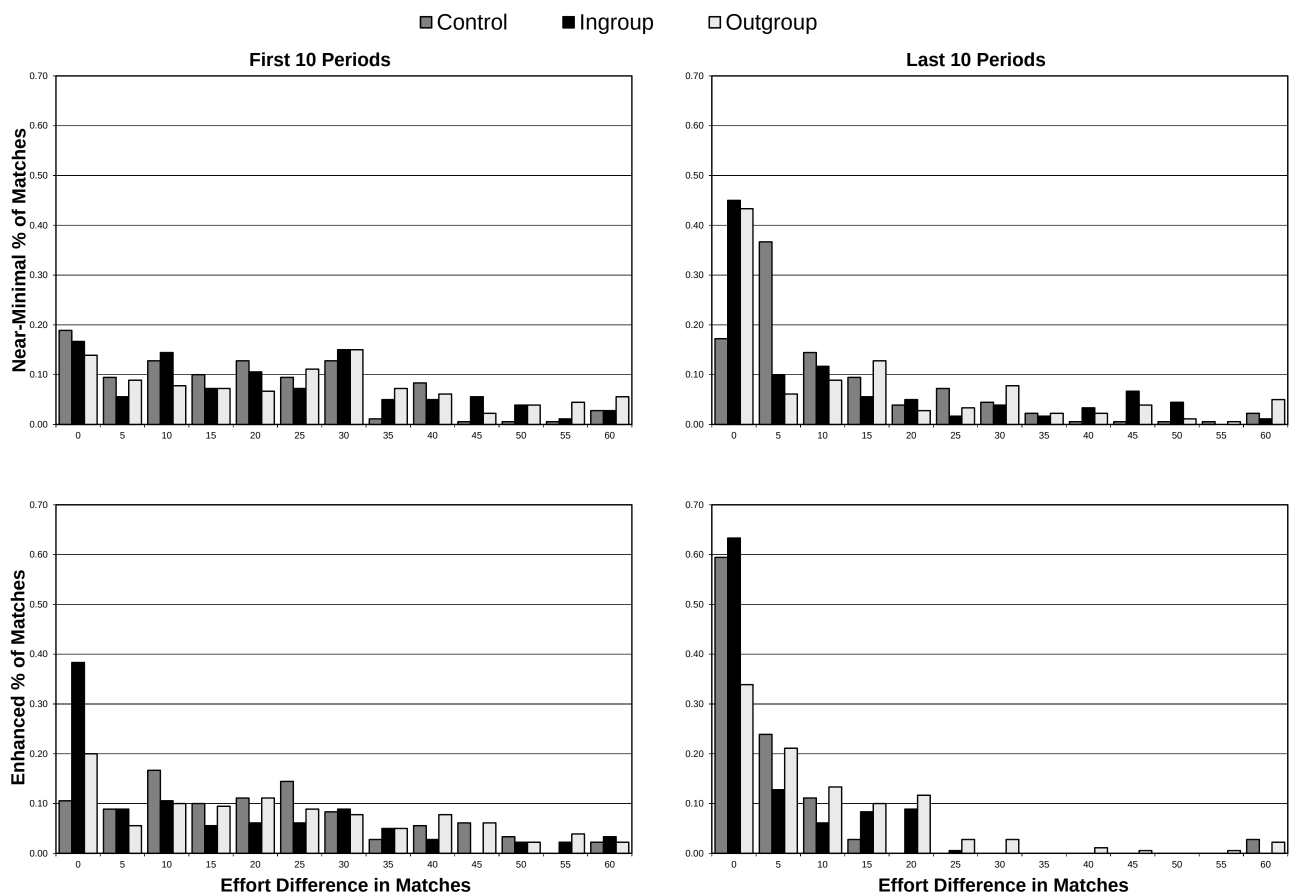

Figure 2: Wasted Effort in each Match for the First 10 Periods (Left Column) and the Last 10 Periods (Right Column), Separated by Near-Minimal (Top) and Enhanced (Bottom) Sessions

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

Result 5 (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 the regression, 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 5 indicates that pairs in different near-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. This result generally supports the predictions of the theoretical model.

Next, we examine efficiency in each treatment, as defined in Section IV. The average efficiency in each session and the overall efficiency in each treatment are presented in Table 8 in Appendix E. To evaluate the statistical significance of the treatment effects on efficiency, we present a random-effects regression in Table 9 in Appendix E. 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.

Consistent with the treatment effects on individual behavior, we find that, in the near-minimal sessions, there is no significant difference in efficiency across the ingroup, outgroup and control treatments ($p > 0.10$ for all pairwise comparisons). Furthermore, in the enhanced sessions, efficiency in the ingroup treatment is significantly higher than that in the control and outgroup treatments ($p < 0.01$). Therefore, 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 5 (column 4) in Appendix A, however, the predicted efficiency in Table 5, e.g., when α approaches 1, is generally lower compared to the actual achieved efficiency, e.g., in the enhanced ingroup treatment (in Table 8 in Appendix E). This is because most of our subjects are able to coordinate on integer values while the computation reported in Table 5 assumes a continuous strategy space.[13] 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.

C Learning Dynamics and Group Identity

While our reduced-form regression analysis establishes the significance of the effect of enhanced group identity on effort, equilibrium selection and efficiency, it does not provide an explanation

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

for the learning dynamics observed in both Figures 1 and 2. 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.

We first examine whether any significant behavioral differences exist in the initial round choices. Using Kolmogorov-Smirnov tests of the equality of distributions for first-round effort choices, 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). Thus, we observe none of the significant treatment effects in the first round.

We now 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 based on history. 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:

$$w_i^{t+1}(x_j) = \delta \cdot w_i^t(x_j) + \begin{cases} 1 & \text{if } x_j = x^t \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

where x^t is the effort level exhibited by player i's match in period t, and δ is the discount factor which gives distant experience less weight than recent ones. Player i's beliefs in period t are then calculated as follows:

$$\mu_i^t(x_j) = \frac{w_i^t(x_j)}{\sum_{x_j} w_i^t(x_j)}. \tag{10}$$

Equation (10) captures player i's beliefs about the likelihood that her match will use each strategy in the upcoming period. These beliefs are then used to calculate player i's expected utility for playing a strategy x_i:

$$\overline{u}^t(x_i) = \frac{1}{(\overline{x} - \underline{x})} \sum_{x_j} [u_i(x_i, x_j) \cdot \mu_i^t(x_j)], \tag{11}$$

where $u_i(x_i, x_j)$ is as defined in Equation (6). 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. Our incorporation of group-contingent social preference into a learning model follows the recent literature (Cooper and Stockman (2002), Arifovic and Ledyard (2009)) which merges the social preference and learning models to explain behavioral regularities in public goods experiments that cannot be satisfactorily explained by either social preference or learning alone.

Using this expected utility, player i determines which strategies are the best for her, choosing strategies with higher expected payoffs more frequently. Specifically, she randomly chooses an effort level x_i with a distribution defined by the following:

$$f_i^t(x_i) = \frac{\exp[\lambda \cdot \overline{u}^t(x_i)]}{\sum_{x_i} \exp[\lambda \cdot \overline{u}^t(x_i)]}, \tag{12}$$

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.

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 perform the calibration in 2 steps. First, 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 0.1.[14] We perform this analysis over all sessions at once. Next, we fix λ and δ at the calibrated values, then recalibrate α^g, allowing the parameter to vary from -1 to 1 in increments of 0.01. This part was performed on the session level. Each calibration consists of the following steps. 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. 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 (9), and calculate the probability distribution of effort levels that the subject is predicted to play according to Equation (12). We then use the quadratic scoring rule to calculate a score for the particular combination of λ, δ, and α^g for each period the subject plays, and sum the period scores in order to obtain a score for that subject. After we have completed this process for every combination of λ, δ, and α^g, we find the parameters that give the highest score (or, in the recalibration, the α^g that gives the highest score in each session).

The results for the analysis are reported in Table 4 in the rows labeled "Near-Minimal" and "Enhanced," with treatment averages reported in the rows labeled "Average." The globally calibrated inverse noise and discount parameters are $\lambda = 3.0$ and $\delta = 0.7$, respectively. 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

[14] The upper bound for λ is based on an initial exploration where we tested fewer values of λ over a larger range.

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 significant ($p = 0.05$). The other comparisons are not significant since every other treatment has one session in which the subjects converge to the efficient equilibrium.

Table 4: α^g Calibration of the Stochastic Fictitious Play Model ($\lambda = 3.0$, $\delta = 0.7$)

Treatments	Sessions	Control	Ingroup	Outgroup
Near-minimal	1	0.26	0.45	0.32
	2	0.28	0.23	0.82
	3	0.68	0.84	0.81
	Average	0.41	0.51	0.65
Enhanced	1	0.07	0.80	0.94
	2	0.87	1.00	0.09
	3	0.00	0.70	0.22
	Average	0.31	0.83	0.42

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 (8). 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 in Appendix E. 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.

VI 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. We also provide a unifying framework for a number of previous experimental studies performed on coordination games in Appendix F.

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 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 derive the comparative statics result that stronger group identification leads to higher effort in equilibrium (Proposition 4), whereas a higher (lower) effort level is assumed to be the exogenous behavioral norm of a worker who identifies (does not identify) with an organization in Akerlof and Kranton (2005). Although our framework captures only a piece of what Akerlof and Kranton call identity, it can explain 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, such as the provision point mechanism. 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 possible direction would be to evaluate the effect of identity-based teams in the field through natural field experiments in fundraising or online communities.

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Appendix A. Theory

(Not For Publication)

Proof of Proposition 1: Maximizing Equation (7) gives us a new threshold marginal cost value, which is a function of the group-contingent other-regarding parameter α_i^g,

$$c^*(n, \{\alpha_i^g\}_{i=1}^n) = \frac{1}{n - \sum_{i=1}^n \alpha_i^g}. \tag{13}$$

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, $u_i^e(x)$,

$$f_i(x) = \frac{\exp(\lambda u_i^e(x))}{\int_{\underline{x}}^{\bar{x}} \exp(\lambda u_i^e(s))ds}, \quad i = 1, \cdots, n, \tag{14}$$

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:

$$u_i^e(x) = \int_{\underline{x}}^{x} y g_i(y)dy + x(1 - G_i(x)) - c[(1 - \alpha_i)x + \alpha_i \int_{\underline{x}}^{\bar{x}} y dF_i(y)], \tag{15}$$

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 (15) can be integrated by parts to obtain:

$$u_i^e(x) = \int_{\underline{x}}^{x} \prod_{k \neq i}(1 - F_k(y))dy - c(1 - \alpha_i)x + c\alpha_i \int_{\underline{x}}^{\bar{x}} F(y)dy + \underline{x} - c\alpha_i\bar{x}. \tag{16}$$

Differentiating both sides of (14) with respect to x and using the derivative of the expected utility in (16), we obtain:

$$
\begin{aligned}
f_i^{'}(x) &= \lambda f_i(x)\frac{du_i^e(x)}{dx} \\
&= \lambda f_i(x)[\prod_{k\neq i}(1-F_k(x)) - c(1-\alpha_i)], \quad i = 1, \cdots n.
\end{aligned} \tag{17}
$$

Using symmetry (i.e., dropping subscripts), further assuming $\alpha_i = \alpha$ for all i, and integrating both sides of (17), 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 (17). 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 (14), the difference in slopes at the crossing is:

$$f_1(x) - f_2(x) = f_1(\underline{x}) - f_2(\underline{x}) - \lambda c(\alpha_2 - \alpha_1)F, \tag{18}$$

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 (18) 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 (8), 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 (8), 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 (8) 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, (8) 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 (17) 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 $M = (\bar{x} - \underline{x})/n$. ∎

Effort and Efficiency Benchmarks:

We use the equilibrium distribution described in Equation (8) 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 5.

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.

Table 5: 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

Appendix B. Experimental Instructions
(Not For Publication)

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-Experimental Survey

(Not For Publication)

(*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*)

Appendix D. Chat Coding Training Session Summary and Instructions (Not For Publication)

D1. Summary of Coding Procedures:

For the line level, the coders are told to take each line of each communication log and sort it into one or more categories. These categories denote whether the line is (a) about the paintings, (b) about the experiment or experimenter, (c) about the subject's group, (d) an expression of excitement, or (e) irrelevant information or none of the other categories. The "paintings" category is further subdivided by whether the line shows (i) painting analysis, (ii) a question about the paintings, (iii) agreement with another participant regarding the paintings, or (iv) disagreement with another participant regarding the paintings. The coders are told that any line can be part of multiple categories.

Next, the coders examine the communication from the subject level. First, for each subject, the coders tell us (a) whether or not the subjects made initial guesses regarding the paintings' artists. In particular, the coders examine whether the subjects (i) made a guess about painting 6, (ii) guessed painting 6 correctly ("Klee"), (iii) made a guess about painting 7, or (iv) guessed painting 7 correctly ("Kandinsky"). We also ask the coders to rate, on a 1 to 5 scale, each subject's level of (b) engagement in the conversation, (c) assertiveness, (d) confidence, and (e) politeness. Finally, the coders examine each communication on a group level (i.e. each communication log as a whole). Again, the coders are asked to rate, on a 1 to 5 scale, each group's level of (a) agreement, (b) confidence, (c) excitement, and (d) politeness.

To ensure that the coders understood their task and the system they would use to complete the coding, we held a training session for the coders. This training session was held on March 1, 2010, and lasted 2 hours. During this session, we first read the instructions out loud, answering any clarifying questions along the way. A copy of these instructions is included in Appendix D. Next, we had the coders examine 2 example communication logs. For this purpose, we obtain communication logs from an experiment conducted by Chen and Li (2009) that used the same paintings and communication procedure as this experiment. After this was completed, the coders were given a week to code the rest of the communication logs. All coding, including the practice coding, was performed on Google Docs. The coders were paid $15 an hour, with a total average payment of $78.

D2. Coding Training Instructions:

You are now taking part in a study that seeks to characterize the communication patterns in chat logs. Your participation will take the form of coding conversations on several factors.

After taking part in this training session, you will code other conversations at home using a web-based system (Google Docs) over the next week. We ask you to not communicate with others about the coding during the course of this week. Should you have any questions while coding on your own, please email me at [email redacted].

The purpose of this training session is to familiarize you with the coding methodology to be employed, and to ensure a common understanding of the factors used. However, this does not mean that you should all give identical codings. We are interested in eliciting objective codings from impartial coders. We ask you to rely on your own judgment when coding.

In the chat logs that you will be coding, the participants were asked to complete a task. First, the participants were divided into 2 groups, named "Red" and "Green" (For the chat logs we will be examining for this training session, the participants were instead in a group called "Maize"). They were shown 5 paintings by Paul Klee and 5 paintings by Wassily Kandinsky (which were labeled 1a, 1b, 2a, 2b, etc.). Then, the participants were given paintings labeled 6 and 7, and were asked to identify which artist painted each painting. These chat logs are the discussions that the participants had with members of their group in order to try to solve this problem.

In this training session you will be asked to code two chat logs. For each chat log, you will be asked to code the conversation at three levels, as shown below:

1. For each line of conversation, code whether it is
   (a) about the paintings. For this category, code whether the line shows
      i. analysis (1 = yes, 0 = no)
      ii. a question (1 = yes, 0 = no)
      iii. agreement with another participant (1 = yes, 0 = no)

iv. disagreement with another partcipant (1 = yes, 0 = no)

(b) about the experiment or experimenter (1 = yes, 0 = no)

(c) about the participant's group (1 = yes, 0 = no)

(d) an expresssion of excitement (1 = yes, 0 = no)

(e) irrelevant information or none of the above categories (1 = yes, 0 = no)

2. For each chat participant, code whether that participant

   (a) made initial guesses about the paintings. For this category, code whether or not the participant

      i. made a guess about painting 6 (1 = yes, 0 = no)

      ii. guessed "Klee" for painting 6 (1 = yes, 0 = no)

      iii. made a guess about painting 7 (1 = yes, 0 = no)

      iv. guessed "Kandinsky" for painting 7 (1 = yes, 0 = no)

   (b) was engaged in the conversation (1 = not engaged at all 5 = very engaged)

   (c) was assertive (1 = not assertive at all 5 = very assertive)

   (d) was confident (1 = not confident at all 5 = very confident)

   (e) had a nice tone towards the other participants (1 = very cold 5 = very warm and friendly)

3. For each chat log, code whether the participants, as a group,

   (a) agreed with each other (1 = no agreement at all 5 = full agreement)

   (b) were confident (1 = not confident at all 5 = very confident)

   (c) were excited (1 = not excited at all 5 = very excited)

   (d) had a nice tone towards each other (1 = very cold 5 = very warm and friendly)

Note that each line of the chat log can be coded into multiple categories. For example, if someone says, "I think that 6 is Kandinsky. What do you think?", this would be coded as painting analysis (1.a.i.) and as painting question (1.a.ii.).

The procedure we will follow in the training session is as follows:

1. First, we ask that you fill out a background questionnaire, included with the papers handed to you in your training packet. Please hand those to [the experimenter] once you have completed them.

2. Next, click on the link to Training Chat 1.

3. You will code Training Chat 1, working individually. Please let us know when you have finished coding the chat log (don't forget the participant-level and group-level categories, located on different sheets of the spreadsheet). If you do not remember the definitions of any of the variables, you can refer to this instruction sheet or the "Coding Category Legend" file. You may ask us questions at any time.

4. When coding variables that are either 0 or 1, we have set the default value to 0. To code any of these variables to be 1, simply change the 0 to a 1.

5. When coding the participant-level variables, you will want to sort the chat lines by the participants so that you can easily see what each participant said during the chat. To do this, click on the cell that says "Participant". Then, click on "Tools", and then click on "Sort sheet by column B, A→Z". To revert to the default line order, click on the cell that says "Line Number", click on "Tools", and then click on "Sort sheet by column A, A→Z".

6. When everyone has completed coding the chat log, there will be a brief discussion, no longer than 30 minutes, regarding the coding activity. We will go over each line, asking each of you for your codings. We will also present our codings and why we coded them the way we did.

7. When all questions have been addressed, you will click on the link to Training Chat 2 and code that chat log.

Are there any questions? Before we start, we would like to ask you to please take the time to read each chat log carefully when coding. We have found that it takes between 15 and 30 minutes to code each chat log when evaluating them carefully. If there are no further questions, let's begin.

Appendix E. Additional Tables
(Not For Publication)

Table 6: Interclass Correlation Coefficients (ICC)

Category	ICC	St. Error
Line Level Coding		
Painting analysis	0.808	0.010
Question about paintings	0.706	0.013
Agreement regarding paintings	0.746	0.012
Disagreement regarding paintings	0.453	0.019
Experiment or experimenter	0.551	0.018
Group	0.550	0.018
Level of excitement	0.553	0.017
Irrelevant (none of the above)	0.622	0.016
Subject Level Coding		
Made a guess about painting 6	0.537	0.058
Guessed Klee for painting 6	0.522	0.059
Made a guess about painting 7	0.585	0.055
Guessed Kandinsky for painting 7	0.609	0.053
Level of engagement	0.744	0.040
Level of assertiveness	0.508	0.060
Level of confidence	0.346	0.064
Level of politeness	0.254	0.064
Group Level Coding		
Level of agreement	0.434	0.159
Level of confidence	0.449	0.157
Level of excitement	0.259	0.160
Level of politeness	0.018	0.126

Table 7: Group Identity and Equilibrium: Probit Regression

$(\Phi^{-1}(\text{equilibrium}) = \beta_0 + \beta_1$*Ingrp+$\beta_2$*Outgrp+$\beta_3$*Ingrp*Enh+$\beta_4$*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 8: 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 9: Group Identity and Efficiency: Random-Effects

(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 10: Effort Distributions

Treatment		Calibrated α^g	Predicted Mean	Predicted SD	Actual Mean	Actual SD
Near-Minimal	Control	0.41	145.65	14.90	133.28	13.07
	Ingroup	0.51	128.91	23.67	148.29	19.18
	Outgroup	0.65	164.37	18.61	157.46	20.96
Enhanced	Control	0.31	137.33	14.89	132.83	27.13
	Ingroup	0.83	139.94	19.09	166.15	6.78
	Outgroup	0.42	157.33	23.61	133.65	25.97

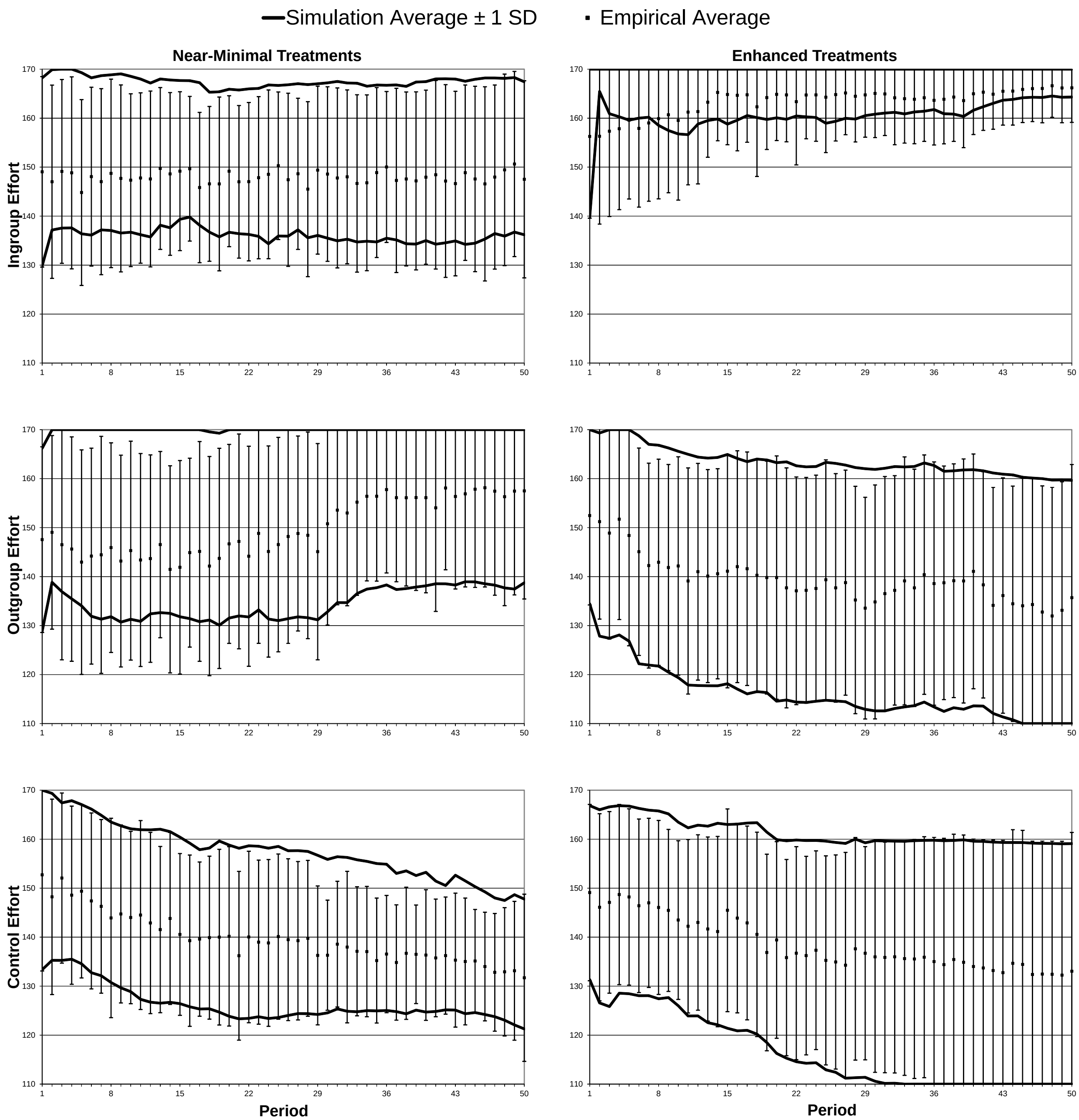

Figure 3: Simulation of Stochastic Fictitious Play (Borders) and Data (Black Dots and Error Bars) in the Ingroup (Row 1), Outgroup (Row 2), and Control (Row 3) Sessions, separated by Near-Minimal (Left Column) and Enhanced (Right Column) Sessions

Appendix F. Reconciling Theory and Experiments

(Not For Publication)

In this appendix, we apply our theoretical framework to previous experimental studies on coordination games, including the minimum-effort games, Battle of the 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.

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 I is shown in Table 11.[15] 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).

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 two-player matches with the third player observing, and then for 5 more periods with all 3 players. The two-player matches establish a group norm of high effort that is consistent with potential theory, which is then transferred to the three-player matches. Allowing the third player to watch the other 2 players

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

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 an 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.[16] 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, 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 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.[17] However, with group competition, it can be transformed into a potential game where the

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

[17]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 maximizing equilibrium is the set of efficient equilibria.

Another well-studied coordination game is the Battle of the 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.

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potential games when $v_1 \neq v_2$.

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Table 11: Summary of Studies Regarding the Minimum-Effort Game (**Not For Publication**)

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