How Does the Real World Impact Laboratory Experiments Measuring Social Preferences? Evidence from the Great Recession*

Raymond Fisman, Pamela Jakiela, and Shachar Kariv†

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Abstract

We compare behavior in modified dictators game during the "Great Recession" to behavior in otherwise identical experiments conducted amidst the economic boom that preceded it. The experiments capture both differences in the indexical selfishness (weight on own payoff) emphasized in other research, and differences in equality-efficiency tradeoffs (concerns for reducing differences in payoffs versus increasing total payoffs). Subjects exposed to the recession exhibit higher levels of indexical selfishness and greater emphasis on efficiency relative to equality. Reproducing recessionary conditions inside the laboratory by confronting subjects with negative payoffs relative to initial endowments intensifies selfishness and increases the willingness to trade equality for efficiency, though the impact is modest relative to that of the real-world economic downturn.

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1 Introduction

A large body of laboratory evidence suggests that subjects in experimental dictator games sacrifice their own incomes to increase the incomes of others.

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†Fisman: Columbia University (email: rf250@columbia.edu); Jakiela: University of Maryland (email: pjakiela@arec.umd.edu); Kariv: University of California, Berkeley (email: kariv@berkeley.edu).

Yet relatively little is known about the extent to which the social preferences that drive giving in the laboratory — where subjects are typically asked to divide *gains* in income — translate into natural decision environments, particularly those involving the redistribution of income, where some parties suffer *losses* relative to their initial endowments. These issues loom particularly large in the current Great Recession, as governments, firms, and households are forced to curtail spending and lay off workers.

Redistributive decisions in standard dictator games are analogous to those that occur in times of rapid growth. Money drops from the sky, and the focus is on who will get the lion's share of the gains. During a recession, redistribution is more defined by shortage and losses relative to past levels — who is going to take the biggest cut compared to last year? Given the different nature of redistributive decisions under conditions of growth versus contraction, it is critical to understand how social preferences are affected by the 'loss' frame of recession versus the 'gain' frame of an economic boom.

In this paper, we compare experimentally-measured social preferences under the vastly different economic conditions that prevailed before and during the sharp downturn sparked by the 2008 financial crisis. We employ the generalized dictator game first utilized by Andreoni and Miller (2002), and further developed by Fisman, Kariv and Markovits (2007), where each subject faces a large and rich menu of budget sets representing the feasible monetary payoffs to $self$ (the subject) and an anonymous *other* subject. Varying the relative prices of redistributing payoffs between $self$ and *other* enables us to identify and distinguish indexical selfishness (the relative weight on the payoff for $self$) from equality-efficiency tradeoffs (the concern for increasing total payoffs versus reducing differences in payoffs). Much of the earlier literature, in contrast, focused exclusively on measuring selfishness.

In addition to conducting identical experiments before and during the downturn, we reproduced recessionary conditions inside the laboratory by confronting subjects with a variant of this modified dictator game where the budget sets were such that either $self$ or *other*, or both, necessarily received a negative payoff relative to their initial endowment. This treatment aimed to generalize the framework of List (2007) and Bardsley (2008), exposing both $self$ and *other* to losses and better reflecting the conditions of scarcity that we wished to emulate in the laboratory. Our design thus allows us to compare the relative impacts of real-world economic conditions versus differing experimental treatments on other-regarding behaviors in the laboratory.

We consider three environments, corresponding to the interaction between the experimental treatment and real-world economic conditions:

- The Gain Boom (GB) environment borrows data from the experiments of Fisman et al. (2007). These data were collected in the fall of 2004, amidst the economic boom that preceded the housing bust and subsequent recession.

- The Gain Recession (GR) environment was identical to GB environment except for minor design modifications; however, these experiments were conducted in the fall of 2011, when the US economy remained mired in the recession that set in during 2008.

- The Loss Recession (LR) environment was identical to the GR environment except that either $self$ or *other* — or both — necessarily experienced a loss relative to their endowment. These experiments were conducted in the fall of 2010 and 2011, in economic conditions similar, sometimes identical, to those of the GR environment.

Unfortunately, we were unable to include a Loss Boom environment since we began the Loss treatment experiments after the economy slid into recession. All experiments were conducted at the Experimental Social Science Laboratory (Xlab) at UC Berkeley. The Xlab draws from a large and diverse group of UC Berkeley students and administrative staff as subjects; we are able to demonstrate that neither changes in the demographic makeup of the UC Berkeley student body nor differences in the selection of Berkeley students into our experiments are likely to drive our results. The experiments generated a rich dataset that provides the opportunity to study the impacts of the environments above on choice behavior at the level of the individual subject.

In the remainder of the introduction, we provide a graphical overview of our findings, which may be summarized as follows: different real-world economic conditions are associated with sharp differences in behavior in the lab. Subjects in the LR and GR environments, who participated in the experiment during the recession, display greater levels of indexical selfishness relative to those in the GB environment, who took part in the experiment during the preceding economic boom. Additionally, subjects in the recession environments, LR and GR, place greater emphasis on efficiency versus equality relative to the subjects in the GB environment. Comparing behavior between the GR and LR environments, we find that the experimental Loss treatment further amplifies these effects, increasing both selfishness and efficiency-orientation. However, its impact is modest when compared to that of real-world economic conditions.

Turning to our visual presentation of the results, Figures 1–3 show different cumulative density functions describing the choices made by subjects in our three environments. A choice of the allocation (π_s, π_o) from the budget set represents the *net* payoffs to persons $self$ and *other*, respectively.[1] The tokens allocated to $self$ as a fraction of the tokens allocated to both $self$ and *other*, $\pi_s/(\pi_s + \pi_o)$, averaged across all budget sets, provides an intuitive univariate measure of altruism. Figure 1 reports, for each environment, the cumulative density function of these individual-level proxies for altruism. Most noticeably, the distribution for the GB environment is skewed sharply to the left, indicating greater overall altruism during a boom relative to the recessionary GR and LR environments. Further, the distributions for the GR and LR environments have sharp jumps at one, indicating a large number of purely selfish and near-selfish subjects, whereas there is no such discontinuity in the GB environment. Finally, the distribution for the GR environment is everywhere slightly above the distribution for the LR environment, implying an incremental — albeit modest — impact of the laboratory Loss treatment on altruism. We thus find evidence that consistent with the view that the experimental treatments have much less of an impact on altruism than the difference in real-world economic conditions.

[Figure 1 here]

We then decompose subjects' social preferences into indexical selfishness and equality-efficiency tradeoffs by estimating constant elasticity of substitution (CES) utility functions

$$u_s(\pi_s, \pi_o) = [\alpha(\pi_s)^\rho + (1-\alpha)(\pi_o)^\rho]^{1/\rho}$$

at the individual level, where α represents the weight on payoffs to $self$ versus *other*, i.e., indexical selfishness, and ρ parameterizes the curvature of the altruistic indifference curves, i.e., equality-efficiency tradeoffs. Any $\rho > 0$ indicates social preferences weighted towards efficiency in the sense of increasing total payoffs, whereas any $\rho < 0$ indicates social preferences weighted towards equality and reducing differences in payoffs.

We emphasize again that our estimation is done for each subject n separately, generating separate subject-level estimates $\hat{\alpha}_n$ and $\hat{\rho}_n$. Figure 2

[1] As in List (2007) and Bardsley (2008), in the Loss treatment, π_s and π_o are equal to the number of experimental tokens earned (positive or negative) plus the initial endowment, so neither $self$ nor *other* can receive a negative net payoff.

presents the distributions of the individual-level $\hat{\alpha}_n$ estimates in the three environments. The patterns closely parallel those of $\pi_s/(\pi_s + \pi_o)$ shown in Figure 1. Turning to the distributions of the estimated $\hat{\rho}_n$ parameters in Figure 3, we find that the distributions for both recessionary environments, GR and LR, are generally skewed sharply to the right relative to the distribution for the GB environment. This indicates that subjects exposed to recessionary conditions lean much more toward an efficiency conception of social preferences. We further note that the ordering of the three distributions is fairly consistent throughout, though at lower percentiles the distribution for the GR environment is much closer to that of the GB environment, while it is very close to the distribution for the LR environment at higher percentiles.[2]

[Figure 2 here]
[Figure 3 here]

Our point of departure from previous work comes from an experimental design that allows for distinguishing indexical selfishness from equality-efficiency tradeoffs, and accurately measuring both in a controlled laboratory setting, under different economic conditions. *Ex ante*, one might expect that recessionary conditions could either increase or decrease the willingness to sacrifice equality to enhance efficiency. Concerns about providing a social safety net might lead to an increased desire to rein in inequality and guarantee a minimum level of income for all, even at the expense of total output, during a recession. Alternatively, conditions of scarcity may make the prospect of leaving money on the table particularly unattractive, leading to an increased focus on efficiency. Our results suggest that this latter concern dominates.[3]

Moreover, by demonstrating the large impact of real-world economic conditions on measured social preferences, our study provides an important contribution to the debate on the role of laboratory experiments in the social sciences, as discussed in Levitt and List (2007), Falk and Heckman (2009), Camerer (forthcoming). As Levitt and List (2007) point out, the relevance of laboratory experiments rests on the assumption that behaviors in the lab are correlated with actions in natural decision environments. We

[2]For subjects with uniformly selfish allocations, $\hat{\rho}_n$ cannot be identified. We therefore screen out purely selfish and near-selfish subjects with average $\pi_s/(\pi_s + \pi_o) \geq 0.99$. We generate virtually identical results with other thresholds for screening on selfishness.

[3]Using survey data, Kuziemko (2011) also finds lower support for redistribution to reduce income differentials during recessions, based on responses to the General Social Survey.

show that real-world economic conditions impact behavior in laboratory experiments measuring social preferences, suggesting that such experiments capture something essential about the way individuals make decisions across a range of settings.

The rest of the paper is organized as follows. Section 2 describes the lab setting and the interactions between experimental treatments and external economic conditions. Section 3 provides the empirical analysis and results and Section 4 concludes by discussing the results and relating them to the broader literature. The paper also includes online data and technical appendices for the interested reader.[4]

2 Experimental Design

In our experiments, we presented subjects with a sequence of modified dictator games, developed by Andreoni and Miller (2002), that vary the relative prices of allocating tokens to $self$ (the subject) and *other* (an anonymous other subject, chosen at random from the group of subjects in the experiment). Each experimental session consisted of 50 independent decision problems. Each problem was presented as a choice from a two-dimensional budget set, using the graphical interface employed by Fisman et al. (2007). Choices were made by using the computer mouse or the keyboard arrows to move the pointer on the computer screen to the desired allocation in the budget set and then clicking or hitting the enter key. The experimental interface makes it possible to present each subject with many choices in the course of a single experiment, yielding a rich individual-level dataset. We may therefore analyze behavior at the level of the individual subject, without the need to pool data or assume that subjects are homogenous. Full instructions, including examples of the computer program dialog windows, are available at Online Appendix I.

As discussed in the introduction, we consider three environments, corresponding to the interaction between the experimental treatment and real-world economic conditions:

- The Gain Boom (GB) environment borrows data from Fisman et al. (2007), collected in the fall of 2004, amidst the economic boom that preceded the Great Recession. In this environment, the axes were scaled from 0 to 100 tokens, and in each decision problem the computer selected a budget set randomly from the set of budget lines

[4]Appendix #: http://emlab.berkeley.edu/~kariv/FJK_I_A#.pdf.

that intersect with at least one of the axes at 50 or more tokens, and with no intercept exceeding 100 tokens.

- The Gain Recession (GR) environment was nearly identical to the GB environment; however, these experiments were conducted in the fall of 2011, as the Great Recession stretched into its fourth year. Additionally, choices were restricted to allocations on the budget constraint. Since most subjects in the GB treatment had no violations of budget balancedness, we made this minor modification to make the computer program easier to use.[5]

- The Loss Recession (LR) environment includes experiments that were conducted in the fall of 2010 and 2011, during conditions of economic stagnation. The experimental design was identical to the GR environment except that subjects each received an initial endowment of 100 tokens, and the axes were scaled from -100 to 100 tokens. In each decision problem, the computer selected a budget line randomly from the set of budget lines that intersected with at least one of the axes at 0 or more tokens, and with no intercept exceeding 100 tokens.

Panel A of Figure 4 illustrates the types of budget lines used in the Loss treatment after the payoffs π_s and π_o are rescaled by the initial endowment of $(100, 100)$. Note that making either $self$ or $other$ better off relative to the initial endowment necessarily creates inequality, while $self$ and $other$ must both be made worse off relative to the endowment in order to produce equality. The Loss treatment generalizes the framework of List (2007) and Bardsley (2008), in which the set of feasible monetary payoff choices of person $self$ is always a line with a slope of -1 that goes through the endowment, which is the neutral reference point of neither taking nor giving. For comparative purposes, Panel B of Figure 4 presents a graphical depiction of the choice sets employed in List (2007). Relative to List (2007), we can think of the budget lines in our experiment changing in two steps. First, since we did not restrict the price ratio to 1, pivot the budget line around the endowment to the randomly-chosen price ratio. Then, shift the pivoted

[5] Of the 76 subjects in the GB environment, 38 subjects (50.0 percent) had no violations of budget balancedness, in that they left no more than one token unspent in any decision problem. If we allow for a less restrictive five token threshold, 64 subjects (84.2 percent) had no violations. Those who did violate budget balancedness also had many revealed preference violations even among the subset of their choices that were on the budget constraint. We discuss the consistency of subjects' choices with revealed preference conditions in greater detail below.

line inward so the endowment is no longer in the feasible set. The pivot gives a “substitution” effect and the shift inward gives an “income” effect.

[Figure 4 here]

In all experiments, payoffs were determined as follows: at the end of the experimental session, the program randomly selected one decision round to determine final payouts. Each round had an equal probability of being chosen. Each subject then received the tokens that he allocated to π_s, and the subject with whom he was matched received the tokens that he allocated to π_o. As in Andreoni and Miller (2002), every subject received two groups of tokens, one based on his own decision to allocate tokens and one based on the decision of another random subject to allocate tokens.[6] In the LR environment, total earnings in each decision problem were equal the number of tokens earned in that period, which could be negative in the Loss treatment, plus the initial endowment of 100 tokens.

All experiments were conducted at the Experimental Social Science Laboratory (Xlab) at UC Berkeley. The subject pool always contains large numbers of subjects, with varying degrees of experience with lab experiments. The subjects in this experiment had no previous experience in experiments of dictator, ultimatum, or trust games at the Xlab. Although the subject pool population consists almost entirely of undergraduate students, within this population it is quite diverse, with subjects from a wide array of majors and disparate socioeconomic backgrounds.

Any substantial changes in the composition of the Xlab subject pool could potentially confound our main findings. We explore this issue in Table 1, where we present characteristics of subjects that participated in sessions during the Boom and Recession economic conditions. For comparison, we also present the same characteristics for the full undergraduate student population at UC Berkeley.

[Table 1 here]

For most attributes, there is no significant difference in the sample composition between the two conditions. The two exceptions are that Boom subjects have slightly lower grade point averages (3.41 versus 3.27, p-value=0.06) and higher rates of enrolment as economics and business majors (0.26 versus 0.11, p-value=0.03). Though marginally significant, the changes in grade

[6]The computer program ensured that the same two subjects were not paired twice as *self-other* and *other-self* — that is, for any pair of subjects n and m, if n passed tokens to m, then n did not also receive tokens from m.

point average are extremely small in magnitude. The decline in the percentage of subjects majoring in economics or business, on the other hand, is quite large. However, given that prior work finds a positive association between studying economics and selfishness and also between studying economics and efficiency orientation, this would create a bias against our results.[7]

3 Analysis and Results

Table 2 summarize the experimental sessions within each treatment. Session-level averages are tightly clustered within each environment, and we do not observe session effects. $\pi_s/(\pi_s + \pi_o)$ averaged 0.772–0.810 in the GB environment, 0.872–0.877 in the GR environment, and 0.898–0.927 in the LR environment. This absence of session effects helps to address concerns about the extent to which our results are driven by changes in the composition of the Xlab subject pool: both the fraction of subjects with California residency and the average GPA vary substantially across sessions within each environment. For example, the percentage of California residents ranges from 61.9 percent to 88.9 percent during the economic boom, and from 67.6 percent to 88.5 percent across the sessions held during the recession. If changes in subject pool demographics were driving our results, we would expect to see large differences in $\pi_s/(\pi_s + \pi_o)$ across sessions within each environment, but we see no evidence of such session-level variation.

[Table 2 here]

In the remainder of this section, we first discuss the revealed preference tests we use to determine whether individual choices in our experiment are consistent with utility maximization. We then discuss results relating to our reduced form measure of altruism, the average fraction of tokens allocated to $self$. Finally, we discuss the impact of recessionary conditions on individual utility parameters — indexical selfishness and the willingness to trade off equality and efficiency — which we estimate at the individual level.

3.1 Revealed Preference

The most basic question to ask about individual choice data is whether it is consistent with utility maximization. Classical revealed preference theory

[7] See Frank, Gilovich and Regan (1993), Fehr, Naef and Schmidt (2006), and Fisman, Kariv and Markovits (2009).

provides a direct test: choices in a finite collection of budget sets are consistent with maximizing a well-behaved (i.e. piecewise linear, continuous, increasing, and concave) utility function if and only if they satisfy the Generalized Axiom of Revealed Preference (GARP). Hence, in order to assess whether our data are consistent with utility-maximizing behavior, we only need to check whether our data satisfy GARP. Because our subjects make choices in a wide range of budget sets, our data provides a stringent test of utility maximization.[8]

Since GARP offers an exact test (either the data satisfy GARP or they do not), we assess how nearly individual choice behavior complies with GARP by using Afriat's (1972) Critical Cost Efficiency Index (CCEI), which measures the fraction by which each budget constraint must be shifted in order to remove all violations of GARP. By definition, the CCEI is between zero and one: indices closer to one mean the data are closer to perfect consistency with GARP and hence to perfect consistency with utility maximization.

In our experiments, mean CCEIs across all subjects are 0.899, 0.944, and 0.938 in the GB, GR and LR environments, respectively. Of our 289 subjects, 128 subject (44.3 percent) were perfectly consistent, 225 (77.9 percent) had CCEI scores above 0.9, and 258 subjects (89.3 percent) had values above 0.8. We interpret these numbers as confirmation that subject choices are generally consistent with utility maximization.[9] Throughout the remainder of the paper, we present results for all subjects and for those with CCEI scores above 0.8 and 0.9 in parallel.

3.2 Preferences for Altruism

Complementing the graphical presentation in Figure 1, Table 3 reports summary statistics and percentile values for $\pi_s/(\pi_s+\pi_o)$, the fraction of tokens allocated to $self$, in each environment, taking averages at the individual level. We present the results for all subjects, as well as for the subsamples

[8]GARP is a generalization of various other revealed preference tests, and is tied to utility representation through a theorem first proved by Afriat (1967). Varian (1982, 1983) replaced the condition Afriat (1967) called cyclical consistency with GARP. We refer the interested reader to Fisman et al. (2007) for precise details on the power of our tests for consistency with GARP.

[9]The fact that choices nearly satisfy GARP implies that subjects had to exhibit stable patterns of choices over the course of the experiment and that the methodology more broadly is easily understood by experimental subjects. In addition, the high consistency scores suggest that incentives were strong enough to maintain subjects' engagement — otherwise, one might expect them to lapse into 'low effort' quasi-random allocations that would generate many violations.

of subjects with CCEI scores above 0.80 and 0.90. The patterns are very similar across different CCEI cutoff thresholds, indicating that the effect of recessionary conditions is not driven by inconsistent subjects.[10] The percentile distributions reported in Table 3 further emphasize that the distribution of $\pi_s/(\pi_s+\pi_o)$ is skewed to the left for subjects in the GB environment, indicating greater overall altruism. Over all prices, the subjects in the GB environment allocated to $self$ 79.3 percent of the tokens; this is very similar to typical mean allocations of about 80 percent in the standard split-the-pie dictator games, reported in Camerer (2003). The recession environments, GR and LR, present a striking contrast, with 87.4 percent and 90.8 percent of the tokens allocated to $self$, respectively.

[Table 3 here]

We next turn to regression analyses that examine the patterns of altruism in the data more systematically. We define indicators for both the Recession condition and the Loss treatment. The dependent variable is the average fraction of tokens allocated to $self$ — the mean of $\pi_s/(\pi_s+\pi_o)$ averaged at the subject level across all decision problems. We report the results of Tobit specifications, which allow for censoring of the dependent variable at zero and one. Table 4 presents the results of the individual-level econometric analysis. In columns (1)–(3), we present the full-sample estimates. In columns (4)–(6) and (7)–(9), we repeat the estimation reported in columns (1)–(3) restricting the sample to subjects with CCEI scores above 0.80 and 0.90, respectively.

[Table 4 here]

Columns (1) and (2) indicate that both Recession and Loss are highly correlated with altruism when employed separately as regressors. When both are included together in column (3), it becomes clear that, while both decrease altruism, most of the effect is through Recession. That is, conditional on recessionary conditions, the experimental Loss treatment has only a marginally negative impact on altruism. The coefficients' magnitudes in column (3) are slightly higher than those suggested by the mean differences in Table 3 above, owing to the censoring adjustment in the Tobit specification. In the subsamples of subjects with CCEI scores above 0.8 and 0.9

[10] We note that the fraction of near-selfish and purely selfish subjects is slightly higher for all environments in the subsamples of subjects with higher CCEI scores, reflecting the fact that selfish subjects — who always allocate all tokens to $self$ — will never have GARP violations.

reported in columns (4)–(9), the point estimates and significance levels are similar, though somewhat higher than for the full sample.

3.3 Indexical Selfishness and Equality-Efficiency Tradeoffs

3.3.1 CES Specification

The revealed preference analysis above shows that choice behavior for most subjects in each of the three environments can be rationalized, in the sense of maximizing a well-behaved utility function. We assume that the altruistic utility function $u_s(\pi_s, \pi_o)$ is a member of the constant elasticity of substitution (CES) family commonly employed in demand analysis. The CES utility function has been used by Andreoni and Miller (2002), Choi, Fisman, Gale and Kariv (2007), and Cox, Friedman and Sadiraj (2008), among others.[11] The primary benefit of the CES formulation is that it makes it possible to distinguish indexical selfishness from equality-efficiency tradeoffs in a particularly convenient manner.

We therefore write:

$$u_s(\pi_s, \pi_o) = [\alpha(\pi_s)^\rho + (1-\alpha)(\pi_o)^\rho]^{1/\rho}.$$

The α parameter measures the indexical weight on payoffs to $self$ versus $other$, whereas the ρ parameter measures the willingness to trade off equality and efficiency in response to price changes. Note that if $\rho > 0$ ($\rho < 0$) a decrease in the relative price of allocating tokens to $self$, p_s/p_o, lowers (raises) the expenditure on tokens allocated to $self$ $p_s\pi_s$; prices are normalized so that $p_s\pi_s + p_o\pi_o = 1$. Thus, any $\rho > 0$ indicates social preferences weighted towards increasing total payoffs, whereas any $\rho < 0$ indicates social preferences weighted towards reducing differences in payoffs.

The CES functional form also spans a range of well-behaved utility functions, approaching a perfect substitutes utility function as $\rho \to 1$ and the Leontief form as $\rho \to -\infty$. As $\rho \to 0$, the CES form approaches log utility, which implies that the expenditures on tokens allocated to $self$ and $other$, $p_s\pi_s$ and $p_o\pi_o$, are equal to fractions α and $1-\alpha$, respectively. Before presenting the estimation, it is important to understand the implications of the CES parameters for individual behavior. Figure 5 illustrates the relationship between the log-price ratio, $\ln(p_s/p_o)$, and the optimal $\pi_s/(\pi_s + \pi_o)$ for different values of α and ρ. An increase in the equality-efficiency parameter ρ

[11] See Levine (1998), Charness and Rabin (2001), Bolton and Ockenfels (2006), Cappelen, Hole, Sorensen and Tungodden (2007), and Bellemare, Kröger and van Soest (2008) for alternative formulations of other-regarding utility functions.

makes the $\pi_s/(\pi_s+\pi_o)$ curve steeper and an increase in the indexical selfishness parameter α shifts the curve upwards. These differences are important in understanding how the CES specification fits the data in the econometric analysis presented in the next section.

[Figure 5 here]

The CES expenditure function is given by

$$p_s\pi_s = \frac{g}{(p_s/p_o)^r + g}$$

where $r = \rho/\left(\rho - 1\right)$ and $g = [\alpha/(1-\alpha)]^{1/(1-\rho)}$. This generates the following individual-level econometric specification for each subject n:

$$p^i_{s,n}\pi^i_{s,n} = \frac{g_n}{(p^i_{s,n}/p^i_{o,n})^{r_n} + g_n} + \epsilon^i_n$$

where $i = 1, ..., 50$ and ϵ^i_n is assumed to be distributed normally with mean zero and variance σ^2_n. Note again that we normalize prices at each observation and estimate demand in terms of expenditure shares, which are bounded between zero and one, with an *i.i.d.* error term. We generate estimates of $\hat{g}_n$ and $\hat{r}_n$ using non-linear Tobit maximum likelihood, and use this to infer the values of the underlying CES parameters $\hat{\alpha}_n$ and $\hat{\rho}_n$.

Before proceeding to estimate the parameters, we emphasize again that our estimations are done for each subject n separately, generating separate estimates $\hat{g}_n$ and $\hat{r}_n$. We also note that when the parameter measuring indexical selfishness $\hat{\alpha}_n$ is large, the parameter measuring equity-efficiency tradeoffs $\hat{\rho}_n$ cannot be separately identified. This will complicate our interpretation of any differences in the distributions of $\hat{\rho}_n$ across treatments, a point we will return to shortly.

3.3.2 CES Results

Figure 6 presents a scatterplot of the estimated $\hat{\alpha}_n$ and $\hat{\rho}_n$ parameters; the individual-level parameter estimates are included in Online Appendix II. The figure shows that there is substantial heterogeneity in both indexical selfishness and preferences toward equality-efficiency tradeoffs. In addition, many subjects have both high $\hat{\alpha}$-values and positive $\hat{\rho}$-values. These subjects are usually selfish, but sacrifice their own payoffs when the relative price, p_s/p_o, is sufficiently high, and they are able to increase to total payoff to $self$ and *other* significantly.

[Figure 6 here]

Table 5 summarizes the distributions of the parameter estimates for each environment. To economize on space, we present only the results for the full sample. The distributions are similar for the subsamples of subjects with CCEI scores above 0.80 and 0.90. The left panel of Table 5 summarizes the estimates $\hat{\alpha}_n$, which parameterizes indexical selfishness. As anticipated, the CES formulation generates very similar results on the correlates of selfishness as our analysis of the average value of $\pi_s/(\pi_s + \pi_o)$ shown in Table 3.

The other panels of Table 5 present the estimates of $\hat{\rho}_n$, which parameterizes attitudes toward equality-efficiency tradeoffs. Since the $\hat{\rho}_n$ parameters of selfish subjects cannot be identified, we screen out near-selfish and selfish subjects using two different thresholds of the average value of $\pi_s/(\pi_s + \pi_o)$, 0.95 and 0.99.[12] The distributions of $\hat{\rho}_n$ in all environments are skewed toward preferences for increasing total payoffs ($0 < \hat{\rho}_n \leq 1$) rather than reducing differences in payoffs ($\hat{\rho}_n < 0$). Nevertheless, the distribution is skewed more to the right for the recession environments, GR and LR, particularly at higher percentiles. Additionally, the distribution for the LR environment is generally skewed right relative to the GR environment, though the two converge at higher percentiles. Finally, the median of $\hat{\rho}_n$ is higher for both recession environments, GR and LR, relative to the GB environment; given the skewed distribution of $\hat{\rho}_n$, the mean values are relatively uninformative. For the two recession environments, the Loss treatment produces a lower median than the Gain treatment.

[Table 5 here]

We now turn to an econometric analysis of the differences in both indexical selfishness and equality-efficiency tradeoffs across environments. Table 6 presents the results of Tobit regressions with the individual-level $\hat{\alpha}_n$ estimates as the dependent variable and Recession and Loss included as covariates. Columns (1)–(3) present the results for all subjects, and columns (4)–(6) and (7)–(9) present the results for subjects with CCEI scores above 0.80 and 0.90, respectively. Our findings closely parallel those of Table 4, which had the average value of $\pi_s/(\pi_s + \pi_o)$ as the outcome variable: the

[12] We note that interpreting the differences in $\hat{\rho}_n$ is complicated by the very fact that the fraction of selfish subjects for whom $\hat{\rho}_n$ cannot be identified differs across environment. The observed differences in $\hat{\rho}_n$ across treatments could occur if the recession had a direct impact on $\hat{\rho}_n$. Alternatively, the differences could result if subjects with low $\hat{\rho}_n$-values were particularly susceptible to selfishness in the GR and LR environments, and hence were selected out of the sample.

RECESSION condition produces a large and significant increase in indexical selfishness, with a modest further increase resulting from the LOSS treatment. These effects increase slightly when subjects with low CCEI scores are screened out of the sample.

[Table 6 here]

Finally, Table 7 presents a range of regression results on the effects of the external RECESSION condition and the laboratory LOSS treatment on equality-efficiency tradeoffs, using the individual-level $\hat{\rho}_n$ estimates as the dependent variable. Since several subjects have very low $\hat{\rho}_n$ values, its distribution is highly skewed. We therefore employ quantile regressions that are less sensitive to extreme values. Further, given the patterns in Table 5 above, which suggest that the effects of the RECESSION condition and the LOSS treatment may be quite different at higher percentiles in the $\hat{\rho}_n$ distribution, we present quantile regressions for the 25^{th}, 50^{th} and 75^{th} percentiles. In all results that follow, we omit subjects whose average $\pi_s/(\pi_s + \pi_o)$ is higher than 0.99, since their efficiency-equity tradeoff parameter $\hat{\rho}_n$ cannot credibly be estimated.

[Table 7 here]

Panel A of Table 7 shows the results of our median regressions. As discussed above, higher values of $\hat{\rho}_n$ indicate a greater focus on efficiency at the expense of equality in payoffs. The full sample results in columns (1)–(3) suggest a modest increase in efficiency-orientation for both the RECESSION condition and the LOSS treatment. However, the extent to which this may be attributed to real-world economic conditions versus the laboratory LOSS treatment is sensitive to the exclusion of subjects with lower CCEI scores, as indicated by the inconsistent patterns across columns (4)–(9). Nonetheless, when both RECESSION and LOSS are included, we can reject the hypothesis that the combined effect is zero with greater than 99 percent confidence for the full sample and also for the subsamples with CCEI scores above 0.80 and 0.90 (p-values 0.003, 0.003, and 0.004, respectively).

Finally, the middle and bottom panels of Table 6 present quantile regressions for the 25^{th} and 75^{th} percentiles, respectively. For the 25^{th} percentile, LOSS is consistently positive and significant in most specifications, whereas RECESSION is generally negative when both covariates are included, though never significant at conventional levels. For the 75^{th} percentile, we find that RECESSION has a positive effect on efficiency orientation. These patterns are consistent with the graphical evidence presented in Figure 3: though the distributions of estimated $\hat{\rho}_n$ parameters from the GR and LR environments are weakly to the right of the GB environment distribution across the range of $\hat{\rho}_n$ values, the LR distribution diverges from the GB distribution at a lower value of $\hat{\rho}_n$ than the GR distribution.

One concern is that results might be driven in part by selection since the RECESSION condition is significantly associated with increases in $\hat{\alpha}_n$, and $\hat{\rho}_n$ cannot be estimated for subjects who always allocate themselves all of the tokens. However, our results are driven in part by an increase in prevalence of subjects with estimated $\hat{\rho}_n$ parameters very close to one. Out of the 61 subjects in the GB environment for whom we were able to estimate $\hat{\rho}_n$, only one had an estimated $\hat{\rho}_n$ above 0.95. In contrast, 7 of 44 (15.9 percent of) estimated $\hat{\rho}_n$ parameters in the GR environment and 13 of 71 (18.3 percent of) estimated $\hat{\rho}_n$ parameters in the LR environment are above 0.95. This striking increase in the frequency of subjects with a very high concern for efficiency is hard to reconcile with selection concerns, which in this case involve a relatively large number of subjects who are screened out of the two recessionary environments.

4 Conclusion

Our main finding is that the Great Recession had a dramatic effect on individual social preferences: subjects who participated in laboratory dictator games prior to the economic downturn are significantly more altruistic than those who took part in identical experiments after the onset of the recession. Our experimental design — employing graphical representations of modified dictator games that vary the price of redistribution — enables us to distinguish indexical selfishness from the willingness to tradeoff equality and efficiency. Moreover, our experimental method generates many observations per subject, and we can therefore analyze both types of social preferences at the individual level. We find that subjects exposed to the economic downturn place greater emphasis on efficiency and display greater levels of indexical selfishness. The experimental LOSS treatment which creates recessionary conditions within the laboratory amplifies these effects, though its influence on social preferences is modest relative to the impact of the real-world economic downturn.

Experimental research has been very fruitful in both establishing the empirical reliability of social preferences and directing theoretical attention to such preferences. We will not attempt to review this large and growing body of work.[13] Instead, we focus attention on the papers that are most relevant to our study. List (2007) and Bardsley (2008) find that including the possibility of taking in a standard split the-pie dictator game increases the proportion of subjects who give nothing. This finding casts doubt on the assumption that decisions in laboratory experiments measuring social preferences are correlated with behavior in common social and economic situations in the real world. As Levitt and List (2007) point out, whether there is a correlation between the real world and behavior in the laboratory is a critical concern for all experimental studies, but particularly those measuring social preferences.

Our results address this concern in two ways. First, our main finding — that exposure to a Recession condition impacts individual social preferences — demonstrates the correlation between behavior in laboratory experiments measuring social preferences and the real world. Second, our Loss treatment extends the design of List (2007) and Bardsley (2008), exposing both subjects to potential losses and varying the price of redistribution. We can therefore test individual behaviors for consistency in domains involving both giving and taking, and better identify the factors denoted as social norms in Levitt and List (2007).

Thus, we take the next step implicitly or explicitly suggested in Levitt and List (2007), Falk and Heckman (2009), and Camerer (forthcoming): we show that social norm changes across environments — experimental treatments and economic conditions — but not across choice sets within an environment; and we use the control offered by the laboratory environment to explore the ways in which economic conditions impact individual behavior.

Researchers have a choice between focusing exclusively on real-world data from large-scale field experiments, or making use of small-scale laboratory data — either on their own, or in conjunction with observational data from outside the lab. The strengths of data from the real world are obvious. On the other hand, if exposure to economic conditions is correlated in a meaningful way with other-regarding behaviors in the laboratory, the clarity that is achieved by putting behavior under the microscope in the laboratory, and shutting down a variety of strategic considerations which can never be turned off in real-world interactions, may well be worth the necessary simplification and the contamination of the "frame" that subjects inevitably put around any experiment.

[13] Camerer (2003) provides a comprehensive, if now somewhat dated, discussion of experimental and theoretical work in economics focusing on dictator, ultimatum and trust games.

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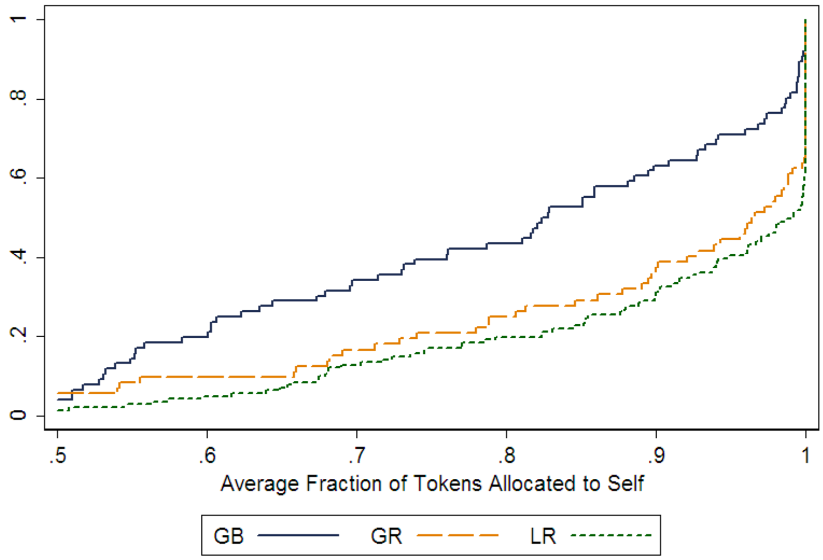
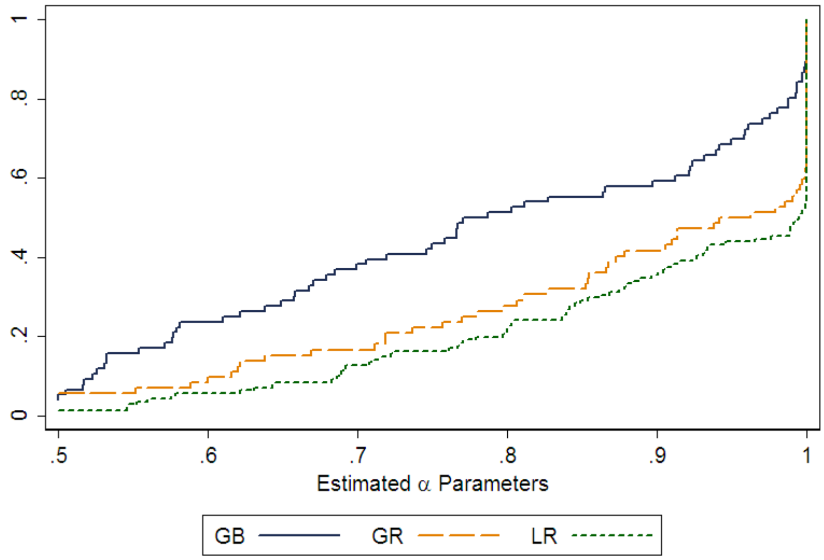
Figure 1: Empirical CDF of Average Fraction of Tokens to *Self*, $\pi_s/(\pi_s+\pi_o)$



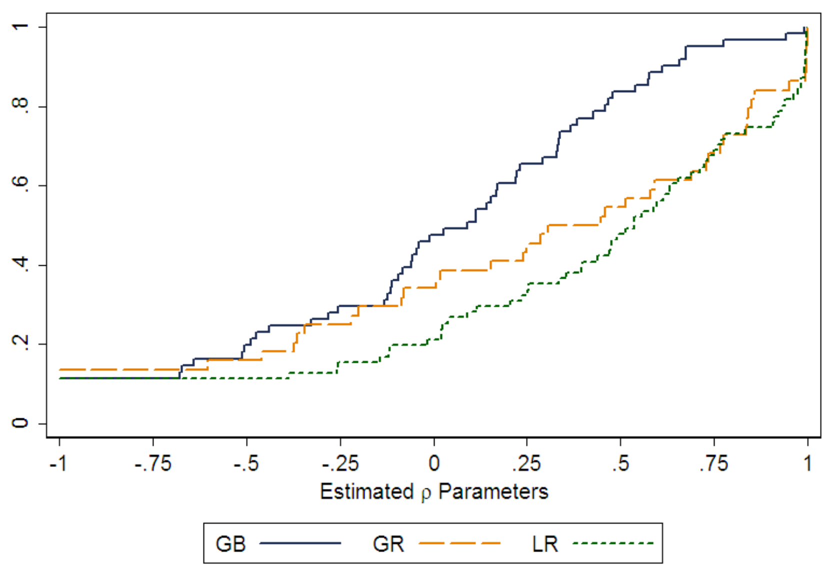
Note: the share of tokens allocated to self is less than 0.5 for 6 of 289 subjects.

Figure 2: Empirical CDF of Estimated $\hat{\alpha}_n$ Parameters



Note: 6 of 289 estimated α parameters are less than 0.5.

Figure 3: Empirical CDF of Estimated $\hat{\rho}_n$ Parameters

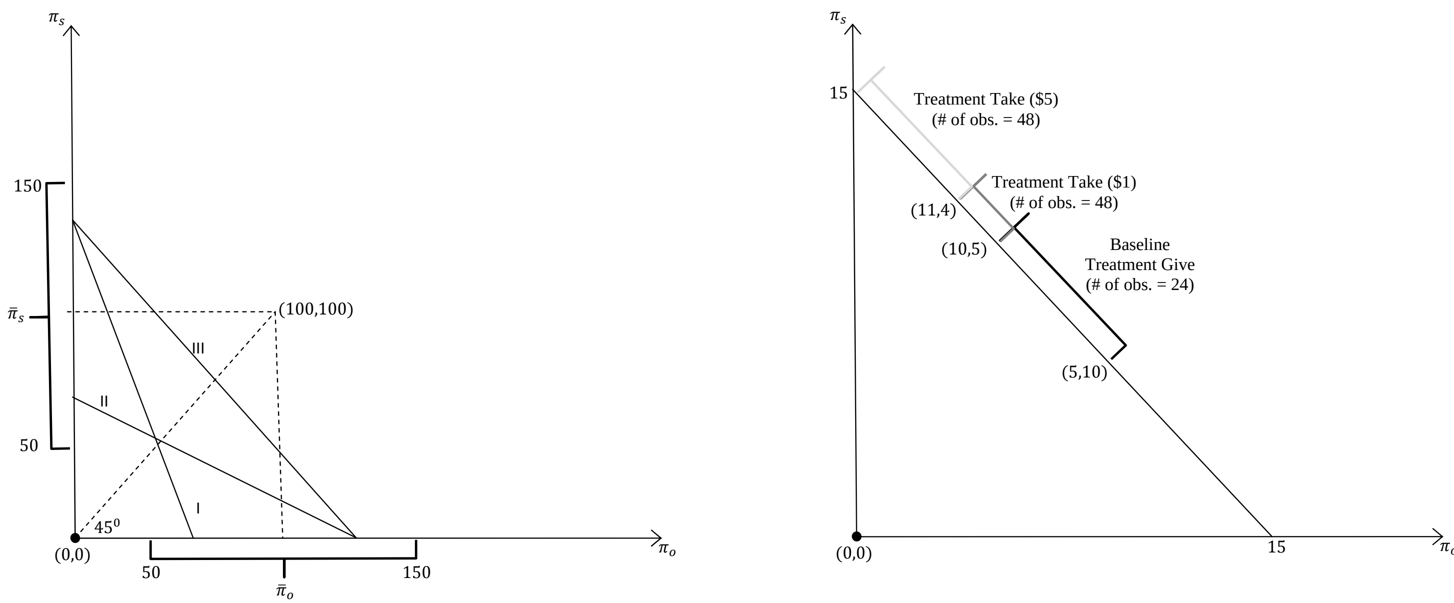


Note: 18 of 176 estimated ρ parameters are less than -1.

Figure 4: Current Experimental Design Compared to List (2007)

Panel A: Current Experimental Design

Panel B: List's (2007) Experiment

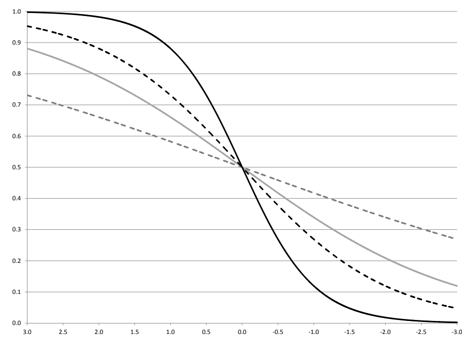


This panel presents examples of budget lines that subjects faced in our experiment. $\bar{\pi}_s$ and $\bar{\pi}_o$ are the endpoints of the budget line, so we can calculate the relative price $p_s/p_o = \bar{\pi}_o/\bar{\pi}_s$. After the payoffs are rescaled by the initial endowment of $(100, 100)$, at least one of the endpoints is above 100 but no endpoint is below 50 or above 150. Given the flat (steep) budget line I (II), $self$ ($other$) must be made worse off relative to the initial endowment in order to increase the total payoff. Given an intermediate budget line III, either $self$ or $other$ must be made worse off relative to the initial endowment. In order to decrease the difference in payoffs, both $self$ and $other$ must always be made worse off relative to the endowment.

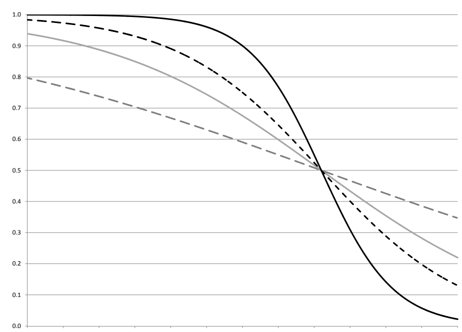
This panel presents the three treatments used by List (2007). In all treatments, the set of feasible monetary payoff choices of person $self$ is always a line with a slope of -1 that goes through the endowment. In each treatment, each subject received an endowment of \$5, and subject $self$ received an additional \$5. In the baseline treatment, $self$ could give to $other$ any fraction his \$5 endowment (in \$0.5 increments). In the other treatments, $self$ could also take either \$1 or \$5 from the \$5 endowment of $other$. Each subject made a single decision. The number of observations per treatment in List (2007) are given in parentheses.

Figure 5: Optimal Fraction of Tokens Allocated to *Self* by Log Price Ratio

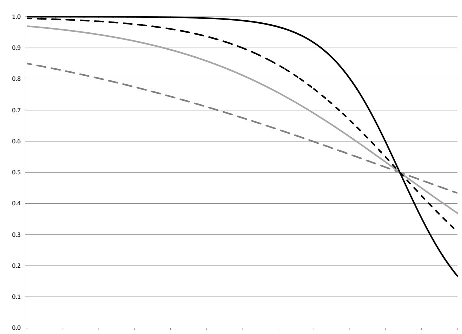
OPTIMAL $\pi_s/(\pi_s + \pi_o)$ WHEN $\alpha = 0.5$



OPTIMAL $\pi_s/(\pi_s + \pi_o)$ WHEN $\alpha = 0.75$



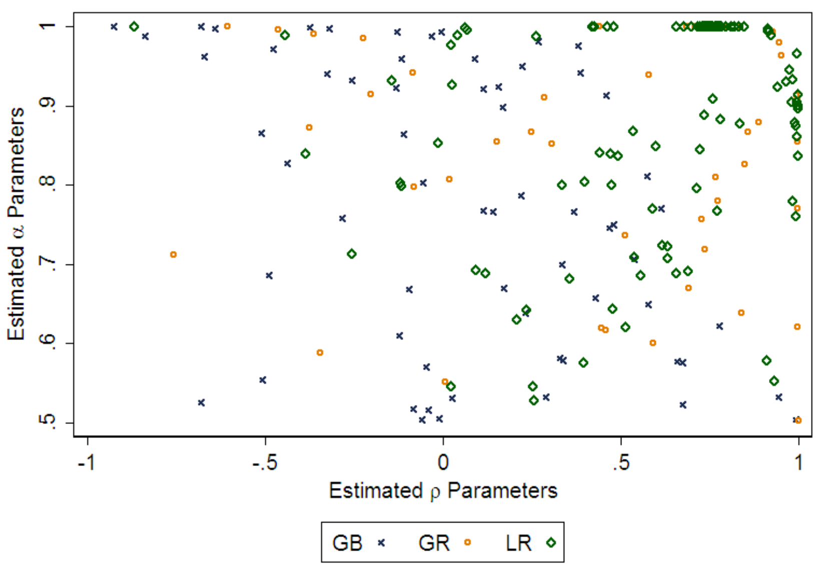
OPTIMAL $\pi_s/(\pi_s + \pi_o)$ WHEN $\alpha = 0.9$



LEGEND

$\rho = 0.5$ $\rho = 0.0$ $\rho = -0.5$ $\rho = -2.0$

Figure 6: Scatter Plot of Estimated $\hat{\alpha}_n$ and $\hat{\rho}_n$ Parameters



Note: 6 α parameters are less than 0.5, and 18 ρ parameters are less than -1.

Table 1: Demographic Characteristics of Experimental Subjects and UC Berkeley Students

CONDITION:	— BOOM —			— RECESSION —			
	SUBJECTS		UCB	SUBJECTS		UCB	
	MEAN	S.D.	MEAN	MEAN	S.D.	MEAN	P-VALUE
Female	0.65	0.10	0.54	0.60	0.11	0.53	0.54
White	0.12	0.06	0.31	0.17	0.09	0.30	0.39
Asian	0.52	0.04	0.41	0.56	0.13	0.39	0.64
CA Resident	0.71	0.15	0.89	0.83	0.08	0.84	0.17
Under 25	0.96	0.06	0.92	0.99	0.02	0.93	0.36
Age of Undergraduates	21.13	1.01	21.40	20.68	0.37	21.30	0.34
Cumulative GPA	3.41	0.14	3.22	3.27	0.05	3.28	0.06
Economics or Business Majors	0.26	0.09	0.06	0.11	0.07	0.07	0.03

SUBJECTS columns include data on participants in our experimental sessions. Data is missing for 23.7 percent of subjects in the BOOM condition and 8.9 percent of subjects in the RECESSION condition. The UCB columns report averages for the entire population of enrolled undergraduates in the Fall terms in 2004 (BOOM condition) and in 2010 and 2011 (RECESSION condition). P-values for t-tests of the equality of subject pool means across the two economic conditions are reported in the last column.

Table 2: Information about Experimental Sessions

				Distribution of $\pi_s/(\pi_s+\pi_o)$	
	Session	Date	Obs.	Mean	95% Conf. Int.
GB	1	09/24/04	24	0.772	[0.703 , 0.841]
	2	09/29/04	26	0.795	[0.720 , 0.870]
	3	10/05/04	26	0.810	[0.732 , 0.887]
GR	4	09/16/11	36	0.877	[0.803 , 0.951]
	5	09/16/11	36	0.872	[0.817 , 0.926]
LR	6	09/01/10	36	0.927	[0.883 , 0.970]
	7	09/01/10	33	0.908	[0.863 , 0.953]
	8	09/16/10	36	0.898	[0.849 , 0.947]
	9	09/16/11	36	0.899	[0.850 , 0.949]

Table 3: Average Fraction of Tokens Allocated to *Self*, $\pi_s/(\pi_s + \pi_o)$

All Subjects

		Environment		
		GB	GR	LR
Mean		0.793	0.874	0.908
S.D.		0.179	0.190	0.136
Percentiles	5	0.510	0.516	0.616
	10	0.531	0.658	0.679
	25	0.614	0.797	0.855
	50	0.826	0.965	0.990
	75	0.974	1.000	1.000
	90	0.998	1.000	1.000
	95	1.000	1.000	1.000
CCEI		0.899	0.944	0.938
Obs.		76	72	141

Subjects with CCEI ≥ 0.8

		Environment		
		GB	GR	LR
Mean		0.798	0.888	0.932
S.D.		0.183	0.181	0.115
Percentiles	5	0.510	0.540	0.680
	10	0.528	0.658	0.736
	25	0.623	0.846	0.901
	50	0.828	0.977	0.998
	75	0.984	1.000	1.000
	90	0.999	1.000	1.000
	95	1.000	1.000	1.000
CCEI		0.951	0.972	0.973
Obs.		65	67	126

Subjects with CCEI ≥ 0.9

		Environment		
		GB	GR	LR
Mean		0.804	0.905	0.949
S.D.		0.188	0.176	0.099
Percentiles	5	0.510	0.528	0.703
	10	0.528	0.681	0.824
	25	0.623	0.896	0.942
	50	0.828	0.987	1.000
	75	0.994	1.000	1.000
	90	1.000	1.000	1.000
	95	1.000	1.000	1.000
CCEI		0.973	0.989	0.988
Obs.		53	60	112

Table 4: Impacts of Environments on Average Fraction of Tokens Allocated to *Self*

Dependent Variable: Average Fraction of Tokens Allocated to Self, $\pi_s/(\pi_s+\pi_o)$

Sample:	All Subjects			CCEI ≥ 0.8			CCEI ≥ 0.9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recession	0.144***	.	0.115***	0.164***	.	0.125***	0.184***	.	0.143***
	(0.026)		(0.035)	(0.028)		(0.037)	(0.032)		(0.04)
Loss	.	0.106***	0.044	.	0.124***	0.059*	.	0.135***	0.063*
		(0.026)	(0.034)		(0.027)	(0.034)		(0.029)	(0.036)
Constant	0.8***	0.855***	0.8***	0.806***	0.868***	0.806***	0.814***	0.888***	0.813***
	(0.022)	(0.018)	(0.022)	(0.024)	(0.019)	(0.024)	(0.028)	(0.02)	(0.028)
Observations	289	289	289	258	258	258	225	225	225
Pseudo R^2	0.347	0.225	0.374	0.431	0.304	0.481	0.416	0.28	0.462

Robust standard errors in parentheses. Tobit regressions adjust for censoring of the dependent variable at zero and one.
$*$, $**$, $***$ indicate 10, 5, 1 percent significance levels, respectively.

Table 5: CES Estimates

Selfishness ($\hat{\alpha}_n$)

All Subjects

		Environment		
		GB	GR	LR
Mean		0.782	0.862	0.900
S.D.		0.188	0.193	0.139
Percentiles	5	0.504	0.502	0.578
	10	0.522	0.616	0.689
	25	0.616	0.775	0.837
	50	0.778	0.952	0.995
	75	0.973	1.000	1.000
	90	1.000	1.000	1.000
	95	1.000	1.000	1.000
CCEI		0.899	0.944	0.938
Obs.		76	72	141

Equality-Efficiency ($\hat{\rho}_n$)

Mean $\pi_s/(\pi_s + \pi_o) < 0.99$

		Environment		
		GB	GR	LR
Mean		-0.321	-0.603	0.114
S.D.		1.604	3.962	1.521
Percentiles	5	-2.786	-2.102	-2.106
	10	-0.838	-1.572	-0.443
	25	-0.326	-0.283	0.024
	50	0.089	0.377	0.535
	75	0.367	0.838	0.908
	90	0.612	0.997	0.992
	95	0.674	0.998	0.997
CCEI		0.875	0.909	0.879
Obs.		61	44	71

Equality-Efficiency ($\hat{\rho}_n$)

Mean $\pi_s/(\pi_s + \pi_o) < 0.95$

		Environment		
		GB	GR	LR
Mean		-0.355	-0.918	0.077
S.D.		1.695	4.598	1.448
Percentiles	5	-4.758	-16.253	-2.106
	10	-1.090	-1.825	-1.117
	25	-0.326	-0.143	0.021
	50	0.070	0.296	0.475
	75	0.367	0.753	0.712
	90	0.658	0.997	0.991
	95	0.776	0.999	0.995
CCEI		0.874	0.892	0.855
Obs.		54	32	57

Table 6: Impacts of Environments on Estimated $\hat{\alpha}_n$ Parameters

Dependent Variable: Estimated $\hat{\alpha}_n$ Parameters

Sample:	All Subjects			CCEI $\geq$ 0.8			CCEI $\geq$ 0.9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recession	0.104***	.	0.077**	0.109***	.	0.076**	0.123***	.	0.096***
	(0.025)		(0.032)	(0.027)		(0.034)	(0.03)		(0.036)
Loss	.	0.079***	0.04	.	0.088***	0.05*	.	0.087***	0.043*
		(0.021)	(0.026)		(0.021)	(0.026)		(0.021)	(0.026)
Constant	0.788***	0.826***	0.788***	0.798***	0.837***	0.798***	0.799***	0.85***	0.798***
	(0.023)	(0.016)	(0.023)	(0.025)	(0.017)	(0.025)	(0.027)	(0.018)	(0.027)
Observations	289	289	289	258	258	258	225	225	225
Pseudo R^2	-0.137	-0.103	-0.155	-0.139	-0.119	-0.168	-0.16	-0.11	-0.18

Robust standard errors in parentheses. Tobit regressions adjust for censoring of the dependent variable at zero and one.
$*$, $**$, $***$ indicate 10, 5, 1 percent significance levels, respectively.

Table 7: **Impacts of Environments on Estimated $\hat{\rho}_n$ Parameters**

Dependent Variable: Estimated $\hat{\rho}_n$ Parameters

Sample:	All Subjects			CCEI ≥ 0.8			CCEI ≥ 0.9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Quantile Regressions of 50th Percentile									
Recession	0.402***	.	0.216	0.4***	.	0.334**	0.378***	.	0.087
	(0.131)		(0.164)	(0.112)		(0.161)	(0.134)		(0.16)
Loss	.	0.381***	0.23	.	0.337***	0.108	.	0.407***	0.35**
		(0.126)	(0.16)		(0.114)	(0.157)		(0.118)	(0.156)
Constant	0.089	0.155*	0.089	0.114	0.219***	0.114	0.219**	0.249***	0.219**
	(0.106)	(0.08)	(0.107)	(0.09)	(0.071)	(0.106)	(0.109)	(0.073)	(0.108)
Panel B: Quantile Regressions of 25th Percentile									
Recession	0.246	.	-0.018	0.174	.	-0.09	0.122	.	-0.281
	(0.189)		(0.24)	(0.22)		(0.257)	(0.243)		(0.219)
Loss	.	0.351*	0.369	.	0.488**	0.579**	.	0.604***	0.835***
		(0.181)	(0.232)		(0.2)	(0.252)		(0.2)	(0.212)
Constant	-0.326**	-0.326***	-0.326**	-0.254	-0.254**	-0.254	-0.083	-0.132	-0.083
	(0.153)	(0.116)	(0.158)	(0.178)	(0.124)	(0.171)	(0.198)	(0.125)	(0.15)
Panel C: Quantile Regressions of 75th Percentile									
Recession	0.472***	.	0.469***	0.376***	.	0.376***	0.371***	.	0.296***
	(0.098)		(0.134)	(0.104)		(0.133)	(0.101)		(0.094)
Loss	.	0.33***	0.072	.	0.24**	-0.003	.	0.259**	0.158*
		(0.11)	(0.13)		(0.121)	(0.131)		(0.108)	(0.091)
Constant	0.367***	0.578***	0.367***	0.46***	0.593***	0.46***	0.479***	0.674***	0.479***
	(0.079)	(0.07)	(0.087)	(0.084)	(0.075)	(0.089)	(0.082)	(0.067)	(0.063)
Observations	176	176	176	145	145	145	113	113	113

Standard errors in parentheses. Quantile regressions reported. $*$, $**$, $***$ indicate 10, 5, 1 percent significance levels, respectively. Sample restricted to subjects with average values of $\pi_s/(\pi_s + \pi_o)$, the fraction of tokens allocated to self, less than or equal to 0.99.