How Did Distributional Preferences Change During the Great Recession?*

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Abstract

To better understand how support for redistributive policies is shaped by macroeconomic shocks, we explore how distributional preferences changed during the recent "Great Recession." We conducted identical modified dictator games during both the recession and the preceding economic boom. The experiments capture subjects' selfishness (the weight on one's own payoff) and equality-efficiency tradeoffs (concerns for reducing differences in payoffs versus increasing total payoffs), which we then compare across economic conditions. Subjects exposed to recession exhibit greater selfishness and higher emphasis on efficiency relative to equality. Reproducing recessionary conditions inside the laboratory by confronting subjects with possible negative payoffs [weakly] intensifies selfishness and increases efficiency orientation, bolstering the interpretation that differing economic circumstances drive our results.

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1 Introduction

The "Great Recession" was accompanied by the rise of *both* the Tea Party and the Occupy Wall Street movements, two groups whose members hold very different views on redistribution — suggesting that economic contraction may polarize opinions on the issue. Whether either (or both) group's successes reflect a causal relationship between macroeconomic shocks and individual support for redistribution is an open question, but one that is difficult to answer empirically. Exogenous variation in exposure to economic contraction is rare and limited in scope, and we cannot conduct large-scale controlled experiments on the US economy. Moreover, many other societal shifts may be coincident with macroeconomic changes, making it difficult to disentangle the effects of different factors which govern the willingness to make tradeoffs between both own and others' income and between equality and efficiency.

In this paper, we explore the relationship between macroeconomic conditions and attitudes toward redistribution by comparing experimentally-measured distributional preferences under the vastly different economic conditions that prevailed before and during the sharp downturn sparked by the 2008 financial crisis. Our experiments 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 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), and to examine how these distributional preferences differ for subjects that participate in the experiment before and after the onset of the financial crisis.

To further test whether the recession is likely to have caused the observed changes in distributional preferences, we simulate economic contraction inside the laboratory by confronting subjects with a variant of our 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.[1] Our design thus also allows us to compare the changes in distribu-

[1] This treatment generalizes the framework of List (2007) and Bardsley (2008), exposing both *self* and *other* to losses and better reflecting the conditions of scarcity that were occurring outside the laboratory. List (2007) and Bardsley (2008) show that the specification of the choice set leads to drastic changes in behavior.

tional preferences that occurred during the real-world recession to the effects of an experimental treatment that simulates recessionary conditions in the laboratory.

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

- The Gain Boom (GB) environment borrows data from the two-person dictator experiment of Fisman et al. (2007), in which the decision problems are presented using a graphical interface that allows for the collection of a rich individual-level data set. The data were collected in 2004, prior to the financial crisis.

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

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

There are four elements to our approach that, we argue, allow us to credibly relate macroeconomic conditions to individual behavior:

First, all experiments were conducted at the Experimental Social Science Laboratory (Xlab) at UC Berkeley. A key benefit of using the Xlab subject pool is that it is drawn primarily from a large and diverse student body, the socioeconomic composition of which is held relatively constant by the admissions office.

Second, we combine administrative and survey data on postgraduate activities to show that the economic prospects of UC Berkeley students were directly affected by the recession. We demonstrate that students faced higher student-loan debts and weakened job prospects during and after the recession than in the preceding years.

Third, we combine demographic and economic data from student admissions and financial aid with a broad range of survey responses about the experience of undergraduates at UC Berkeley. Using these data, we demonstrate that, despite the recession's impact on students' financial circumstances and job prospects, the makeup of the student body, students' overall social and academic experiences, opinions about student life, and perceptions of campus climate fluctuated very little over the period we study.

Fourth, the final piece of our analysis involves the Loss treatment that simulates recessionary conditions in the laboratory. As we describe below, we find that the impact of this experimental treatment is directionally the same as that of the real-world recession (though the effect of Loss on selfishness is not consistently significant). This bolsters the view that economic conditions, rather than other concurrent social or political changes, are likely behind the shifts in distributional preferences we observe in recession versus boom years.

Following Andreoni and Miller (2002) and Fisman et al. (2007), we estimate constant elasticity of substitution (CES) utility function over the payouts to *self* and *other*, which makes it possible to distinguish indexical selfishness from equality-efficiency tradeoffs in a particularly convenient form. The rich data generated by the design allow us to analyze behavior at the level of the individual subject.

Our main findings are as follows: subjects in the LR and GR environments, who participated in the experiment during the downturn, place greater emphasis on efficiency versus equality 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, display greater levels of indexical selfishness relative to the subjects in the GB environment.

Comparing behavior between the GR and LR environments, we find that the experimental Loss treatment also increases both selfishness and efficiency-orientation (though its impact is relatively modest). Thus, overall we find that both real-world and lab-simulated recessionary conditions are associated with shifts in distributional preferences toward greater selfishness and efficiency focus. These results are robust to the inclusion of session-level demographic and socioeconomic controls.

Ex ante, one might expect that recessionary conditions could either increase or decrease the willingness to sacrifice equality to enhance efficiency. During a recession, 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. 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. As Saez and Stantcheva (2013) point out, optimal taxation depends on the distributional preferences of taxpayers. Our results highlight the potentially complex interrelationship between the business cycle and the distributional preferences of voters.

To the best of our knowledge, there is only a small body of work on the impact of economic conditions on distributional preferences. Using surveys fielded between 2007 and 2011, Margalit (2013) studies how respondents' attitudes toward redistributive policies change in response to economic shocks: a drop in household income, a (subjective) decrease in employment security, and the actual loss of a job all increase support for government welfare programs. By contrast, Kuziemko (in progress) finds lower support for government redistribution during recessions, based on responses to the General Social Survey. By studying the willingness to make real tradeoffs between equality and efficiency in a controlled environment, our experimental design partially addresses the problems of interpretation that hamper such survey-based research.[2]

The rest of the paper is organized as follows. Section 2 describes the structure of the decision experiments and the interactions between experimental treatments and external economic conditions. Section 3 describes the subject pool and addresses a number of concerns regarding identification. Section 4 provides the empirical analysis and results, and Section 5 concludes by discussing the results and relating them to the broader literature.

2 Experimental Design

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). Throughout, we denote persons *self* and *other* by s and o, respectively, and the associated payoffs by π_s and π_o.

In a typical dictator experiment, *self* divides an endowment of tokens between $self$ and *other* in any way he wishes such that $\pi_s + \pi_o = 1$ (without loss of generality, the endowment is normalized to 1). One respect in which this framework is restrictive is that the set of feasible payoff pairs is always

[2] Our paper is also related to the subfield of development economics that examines how individual preferences are affected by exposure to violence civil and conflict. For example, Voors, Nillesen, Verwimp, Bulte, Lensink and Van Soest (2012) examine the impact of Burundis conflict on distributional, risk, and time preferences, and Callen, Isaqzadeh, Long and Sprenger (2014) investigate the consequences of violence for economic risk preferences in Afghanistan.

the budget line with a slope of -1, so that the problem faced by *self* is simply dividing a fixed total income between *self* and *other*.

In the modified dictator game we study, *self* allocates the tokens across (π_s, π_o) at corresponding prices (p_s, p_o), such that $p_s\pi_s + p_o\pi_o = 1$; he can choose any allocation $(\pi_s, \pi_o) \geq 0$ that satisfies this constraint. We denote the endpoints of the budget line as $\bar{\pi}_s$ and $\bar{\pi}_o$ so we can calculate the relative price $p_s/p_o = \bar{\pi}_s/\bar{\pi}_o$. Varying the relative price of redistribution p_s/p_o allows us to examine individual responses to price changes. An example of a budget line in our experiment is the straight line AB drawn in Figure 1. In this example, $p_s > p_o$. Selfish preferences $u_s(\pi_s, \pi_o) = \pi_s$ are consistent with allocation A, utilitarian preferences $u_s(\pi_s, \pi_o) = \pi_s + \pi_o$ are consistent with allocation B, and Rawlsian or maximin distributional preferences are consistent with allocation C which lies on the diagonal. Cobb-Douglas distributional preferences $u_s(\pi_s, \pi_o) = \pi_s\pi_o$ are consistent with allocation D which is the centroid of a budget line so that equal budget shares are spent on *self* and *other* $p_s\pi_s = p_o\pi_o$.

[Figure 1 here]

Each experimental session consisted of 50 independent decision problems; each problem was presented as a choice from a two-dimensional budget line, using the graphical interface employed by Fisman et al. (2007). For each decision problem, the computer program selected a budget line at random.[3] Subjects made their choices by using the computer mouse or keyboard arrows to move the pointer to the desired allocation, (π_s, π_o), and then clicked the mouse or hit the enter key to confirm their choice. Full experimental instructions, including screen shots of the decision problems in each treatment, are provided in the Online Appendix.[4,5]

[3] In Online Appendix Figure 1, we present histograms of log price ratios for each of the three environments. Pairwise Wilcoxon rank-sum tests fail to reject the equality of the distributions of log prices across the three environment (pairwise p-values: 0.838 for GB vs. GR, 0.855 for GB vs. LR, and 0.786 for GR vs. LR).

[4] At the beginning of each decision round, the experimental program dialog window went blank and the entire setup reappeared. The appearance and behavior of the pointer were set to the Windows mouse default. At the beginning of each round, the pointer was automatically repositioned at the origin $(\pi_s, \pi_o) = (0, 0)$ in the GB environment and repositioned randomly on the budget line in the GR and LR environments.

[5] One concern with our research design is that presenting choices graphically may somehow bias behavior. Aside from the graphical presentation of choice problems, the Gain treatment is identical to Andreoni and Miller (2002), so the results are directly comparable. Although we test a much wider range of budget sets than can be tested using the pencil-and-paper questionnaire method of Andreoni and Miller (2002), the behaviors elicited graphically are consistent with those elicited non-graphically.

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. Varying the relative price of redistribution allows us to decompose each subject's distributional preferences into two distinct components: fair-mindedness and equality-efficiency tradeoffs. Subjects who increase the fraction of the budget spent on *other* as the relative price of redistribution increases have distributional preferences weighted towards equality (reducing differences in payoffs), whereas those who decrease the fraction of the budget spent on *other* when the relative price of redistribution increases have distributional preferences weighted toward efficiency (maximizing the average payoff).

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; in other words, the maximum payoff that *self* or *other* could receive was always between 0 and 100 tokens. In each decision problem the computer selected a budget line randomly from the set of budget lines that intersect with at least one of the axes at 50 or more tokens.

- The Gain Recession (GR) environment was nearly identical to the GB environment; however, these experiments were conducted in the fall of 2011, amidst the economic malaise that followed the financial crisis. 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.[6]

[6] In the GB environment, choices were not restricted to allocations on the budget constraint, but very few subjects violated budget balancedness by choosing strictly interior allocations. If we allow for a five token margin to account for small mistakes resulting from the slight imprecision of subjects' handling of the mouse, 84.2 percent of subjects had no violations of budget balancedness. Of those, 38 subjects (50 percent) left no more than one token unspent in any decision problem. The few subjects 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.

- The LOSS RECESSION (LR) environment includes experiments that were conducted in the fall semesters 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.

Figure 2 illustrates the types of budget lines used in the LOSS treatment after the payoffs to *self* and *other*, π_s and π_o, are rescaled by the initial endowment of $(100, 100)$ so that the total payoff including the initial endowment is positive. Numbers on the axes represent the sum of the initial endowment of $(100, 100)$ plus the payoff from the dictator game. After the payoffs are rescaled by the initial endowment, at least one of the endpoints $(\bar{\pi}_s, \bar{\pi}_o)$ of each budget line is above 100, but no endpoint is below 50 or above 150. Given the steep (resp. flat) budget line I (resp. II), *self* (resp. *other*) must be made worse off relative to the initial endowment in order to increase the total payoffs. 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.[7]

[Figure 2 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.[8] 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.[9]

[7]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.

[8]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. 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.

[9]One concern with the payout method is that it may create a sense of reciprocity

3 Subject Pool Composition

A potential concern with our research design is that differential selection across the Boom and Recession economic conditions, or factors other than the recession, may be driving our results. To this end, we combine detailed administrative and survey data and show that students' economic prospects, in the form of job offers, employment rates, and salaries at graduation, were significantly worse in 2010 and 2011 than in 2004. At the same time, all other aspects of the Berkeley student population's socioeconomic circumstance, social life, and academic experiences were essentially unchanged.[10] When we focus on the data available on subjects in our sample, we similarly find no shift in background attributes. We argue that these results, especially when combined with our findings on subject behavior in the Loss treatment, support the view that economic conditions likely account for the shift in distributional preferences observed in our data.

3.1 Socioeconomic and Demographic Composition

All experiments were conducted at the Xlab at UC Berkeley. The Xlab draws its subjects from a large and diverse group of UC Berkeley students and administrative staff; but most participants in Xlab experiments are undergraduate students. To explore how the sample of participants may have shifted across years, we test whether the observable characteristics of Berkeley students overall, or those who participated in our experiments specifically, differ across the Boom and Recession conditions.

3.1.1 UC Berkeley Student Body

The Online Appendix provides a graphical presentation of the make-up of the UC Berkeley student body during 2004–2011. Students' self-reported family incomes fluctuated only a small amount: adjusted for inflation, the fraction of students whose families earn less than $80,000 a year increased from 52.3 percent in 2004 to 53.0 percent in 2010, while those whose families

amongst subjects, as they all are both givers and receivers of tokens. Previous studies suggest that this is unlikely to be a major issue: in both Andreoni and Miller (2002) and Fisman et al. (2007), the fraction of income kept by subjects is about 80 percent, similar to the average reported by Camerer (2003) in a summary of earlier dictator games. We return to this issue in the Analysis and Results Section below.

[10] We utilize datasets from UC Berkeley's Office of Planning and Analysis, Financial Aid and Scholarships Office, Career Center, Cal Answers (Student Data Warehouse), and the University of California Undergraduate Experience Survey (UCUES), a system-wide survey on the experiences of undergraduate students at the University of California.

earn \$80,000–\$150,000 decreased from 29.1 percent to 26.8 percent (see Online Appendix Figure 2). In addition, the fraction of UC Berkeley students receiving Federal Pell Grants increased from 33.3 in 2004 percent to 35.6 percent in 2011 (see Online Appendix Figure 3).[11]

With regard to ethnic diversity, the fraction of under-represented minority students (African Americans, Chicanos/Latinos, and Native Americans) also shows only a small change, increasing from 14.8 percent to 16.2 percent over the period (see Online Appendix Figure 4). Finally, the distribution of self-reported social classes when growing up has remained virtually unchanged year to year (Online Appendix Figure 5).

Overall, these data show that UC Berkeley students come from diverse socioeconomic backgrounds. Nevertheless, the distributions of student backgrounds have remained virtually unchanged, despite the unprecedented budget shortfall that resulted from the recession. While the recession has touched many Americans and possibly impacted their decisions to attend college, the composition of UC Berkeley undergraduates is less vulnerable to fluctuation, possibly due to the care with which the socioeconomic makeup is managed by the admissions office.

3.1.2 Experimental Subjects

Though the overall composition of the student body changed little over the period when we conducted our experimental sessions, any substantial changes in the composition of our subject pool could also potentially confound our main findings. The Xlab participant pool always contains large numbers of subjects. 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. We explore the composition of our subject pool in Table 1, where we present characteristics of subjects that participated in sessions during the Boom and Recession economic conditions. Due to privacy concerns, we were able to obtain only session-level averages of subject attributes (so we cannot control for individual attributes in our analysis). For comparison, we also present the same characteristics for the full undergraduate student population at UC Berkeley.

[11] The Federal Pell Grant program provides awards of up to \$5,550 per academic year for financially eligible undergraduate students (family incomes generally less than \$45,000 a year). Students with household incomes of less than \$80,000 pay no tuition under UC's Blue and Gold Program. The Middle Class Access Plan sets a 15 percent cap on parental contributions for families with gross income from \$80,000 to \$140,000 annually.

We begin by observing that there is substantial (random) variation across sessions within each time period in observable characteristics (as indicated by the relatively high standard deviations listed in Table 1). If unobserved attributes similarly varied across sessions in such a way as to affect subjects' decisions, we would expect to see more variation across sessions within a given time period than we find in the data. This narrows the set of likely explanations for the patterns we observe to things that change over time, rather than individual characteristics.

Further, 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 higher 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 change in grade point average is quite 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 likely creates a bias against our results.[12]

[Table 1 here]

3.2 The Impact of the Recession on UC Berkeley Students' Economic Prospects

Though UC Berkeley is one of the best universities in the United States, its students were by no means immune to the effects of the Great Recession. Every year the UC Berkeley Career Center conducts a survey of the postgraduate activities of Bachelor's degree recipients. The data show that in more recent years, students faced greater financial challenges after graduation, with job offers declining and real salary growth stagnating after the onset of the financial crisis. As indicated in Figure 3, the number of job offers received by graduation declined across all majors, with an overall campus average of 2.1 in 2004-2007 versus 1.8 in 2008-2011. Similarly, as indicated in Figure 4, the initial postgraduate employment rate declined across all majors, with an overall campus average of 50.6 percent in 2004-2007 versus 41.6 percent in 2008-2011. Finally, as we observe in Figure 5, real salary

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

growth declined post-2008 for graduating students in most majors, with the average growth rate across all fields falling from 2.0 percent to 0.6 percent.[13]

[Figure 3 here]
[Figure 4 here]
[Figure 5 here]

3.3 Other Shifts in UC Berkeley Student Life

There were clearly many changes that impacted the lives of Berkeley students between 2004 and 2011 outside of the recession. A number of political events have deeply affected American society, including the wars in Iraq and Afghanistan, the election of Barack Obama, and the passage of significant social legislation on healthcare and gay marriage. The very nature of social interaction has also changed through the increased use of social networking platforms and the ever greater sophistication of smart phones. It is obviously impossible to disentangle the effects of different factors on distributional preferences or to identify causal relationships in a dispositive way. At the same time, we observe surprisingly few changes in students' attitudes and campus experiences, as might have been predicted if (non-economic) societal shifts were responsible for the changes in distributional preferences that we observe.

We explore changes in campus conditions and attitudes using the UCUES data. The UCUES collects a broad range of data about the experience of undergraduate students at the University of California. It provides information about student behaviors and attitudes and many different aspects of campus life.[14] Despite the economic downturn, the data from the UCUES show that students' overall experience, their opinions on student life, and their perceptions of campus climate fluctuated very little from 2004 to 2011, the

[13] These patterns echo the findings of Oreopoulos et al. (2012) on the career effects of graduating from college during a recession. In particular, they find that recessions lead to higher unemployment and lower wages, resulting in substantial reductions in the financial returns to college education. The data of Oreopoulos, von Wachter and Heisz (2012) cover the majority of Canadian college students from 1976 to 1995, and individual income tax records and payroll information from 1982 to 1999. The data also include a great deal of individual-level demographic and economic information. Canada experienced two major recessions in the period under study, in the early 1980s and 1990s.

[14] The UCUES collects background information not available through other student data sources. None of the national surveys of undergraduates such as the National Survey of Student Engagement (NSSE) offers the same coverage of student population as the UCUES. For more information, see http://studentsurvey.universityofcalifornia.edu/.

period when we conducted our experimental sessions. Despite UC Berkeley's unprecedented budget shortfall, students' self-reported overall social and academic experiences have remained unchanged during 2004-2011 (see Online Appendix Figures 6 and 7). The UCUES data also show that student behaviors including time allocation, interactions with other students, and community involvement fluctuated surprisingly little over the period.

Thus, while we cannot rule out the possibility that factors other than the recession account for the differences in subjects' behaviors across economic conditions, there is no evidence that the subject pool has shifted in other observable ways across our experimental sessions.

4 Analysis and Results

Our main outcome 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. 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.

Table 2 summarizes 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 lack of variation within each environment suggests that variation across sessions is not being driven by variation in the observable characteristics of subjects, which vary substantially across sessions within each environment, or by campus-wide shocks that happen to coincide with particular sessions.[15]

[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 report results relating to our reduced form measure of overall altruism, the average fraction of tokens allocated to *self* $\pi_s/(\pi_s + \pi_o)$. Finally, we discuss the impact of recessionary conditions on individual utility parameters — indexical selfishness and the

[15]We explore this point further in our main analysis by including session-level controls in our regressions specifications.

willingness to trade off equality and efficiency — which we estimate using constant elasticity of substitution demand functions at the individual level.

4.1 Revealed Preference

The most basic question to ask about individual choice data is whether it is consistent with utility maximization. Classical revealed preference theory provides a direct test: choices in a finite collection of budget sets are consistent with maximizing a well-behaved (piecewise linear, continuous, increasing, and concave) utility function if and only if they satisfy the Generalized Axiom of Revealed Preference (GARP). 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.[16] 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.

4.2 Data Overview

We begin with a graphical overview of our results. Figure 6 reports, for each environment, the cumulative density function of the average value of $\pi_s/(\pi_s + \pi_o)$, calculated at the subject level. 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

[16] 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.

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.

[Figure 6 here]

Complementing the graphical presentation in Figure 6, Table 3 reports summary statistics and percentile values for $\pi_s/(\pi_s + \pi_o)$ in each environment, taking averages at the individual level. We present the results for all subjects, as well as for the subsamples 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.[17] 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 79.3 percent of the tokens to *self*; 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 GR environment presents a striking contrast, with 87.4 percent of the tokens allocated to *self*, while the LR environment causes a further increase to 90.8 percent.[18]

[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 economic condition and the Loss experimental 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. Because our independent variables of interest vary at the session level,

[17]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.

[18]Engel (2011) presents a meta-study of 129 dictator games conducted between 1992 and 2009. The mean allocations in these studies are of about 72 percent, but the analysis is not directly comparable because it includes a diverse set of experimental treatments. Engel (2011) does not report the relationship between real-world economic conditions and behaviors in the laboratory.

we report OLS specifications clustered by session and generate p-values using the Wild cluster bootstrapping procedure described in Cameron, Gelbach and Miller (2008) and Cameron and Miller (forthcoming) to correct for the small number of sessions.[19] Panel A of Table 4 presents our results. 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), we observe that both are significantly associated with lower altruism, though the estimated impact of the Recession is more than twice as large as the impact of the estimated Loss treatment. In the subsamples of subjects with CCEI scores above 0.8 and 0.9 reported in columns (4)–(9), the point estimates and significance levels are similar, though somewhat higher than for the full sample.

In Panel B, we replicate the analysis including session-level demographic and economic controls.[20] We were unable to obtain individual-level data from our subjects, but we were given access to session-level demographic information, and we include controls for the percent of subjects in each session who are California residents, the percent Caucasian, and the percent Asian-American (African Americans and Hispanics are the omitted category). In addition, for each session we were provided with a list of zip codes for the subjects' permanent addresses. We use these data to calculate the median income in 2000 in the zip code of subjects' permanent addresses, and average these figures over each session as an additional control. As Panel B of Table 4 demonstrates, including these controls has almost no impact on estimated coefficients, suggesting that our results are unlikely to be driven by changes in the demographic composition of either the UC Berkeley student body or the Xlab subject pool.

[19] In Online Appendix Table 1, we present comparable Tobit specifications which adjust for censoring of the dependent variable at zero and one. Point estimates and significance levels are similar to OLS; however, since the Tobit standard errors are not corrected for the small number of clusters, they should be interpreted with caution.

[20] Matching individual-level characteristics to decisions within the experiment would require us to seek informed consent (by mail) from our subjects. Response rates for this type of solicitation tend to be very low, and we expect this to be the case especially for participants in the 2004 sessions, who have long since graduated.

4.3 Indexical Selfishness and Equality-Efficiency Tradeoffs

4.3.1 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.[21] 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 share of the 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 distributional preferences weighted towards increasing total payoffs, whereas any $\rho < 0$ indicates distributional 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 7 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

[21] If individual choices satisfy GARP, Afriat's (1967) theorem tells us that there exists an increasing, continuous and concave utility function that rationalizes the data. Additionally, in the case of two goods, consistency with GARP and budget balancedness implies that the demand function is homogeneous of degree zero. Separability and homotheticity then entail that the underlying utility function will have the CES form. The CES utility function has been used by Andreoni and Miller (2002), Fisman et al. (2007), and Cox, Friedman and Sadiraj (2008), among others. See Levine (1998), Charness and Rabin (2002), 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 7 here]

The CES expenditure function is given by

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

where

$$r = \rho / (\rho - 1) \text{ and } g = [\alpha/(1-\alpha)]^{1/(1-\rho)}.$$

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 individual-level 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 equality-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.

4.3.2 CES Results

Figure 8 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 6. Turning to the distributions of the estimated $\hat{\rho}_n$ parameters in Figure 9, we find that the distributions for both recessionary environments, GR and LR, are skewed 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 distributional preferences, with a further shift toward efficiency in the Loss treatment. 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.[22]

[Figure 8 here]
[Figure 9 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 of $\hat{\alpha}_n$, 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.[23] 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. 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.

[22] 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.

[23] 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.

[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 OLS 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 Recession condition produces a large and significant increase in indexical selfishness, with a somewhat smaller additional increase resulting from the Loss treatment.[24] These effects increase slightly when subjects with low CCEI scores are screened out of the sample.

[Table 6 here]

Finally, Table 7 presents our regression results on the effects of the external Recession condition and the laboratory Loss treatment on equality-efficiency tradeoffs. Since several subjects have very low $\hat{\rho}_n$ values, its distribution is highly skewed. We therefore focus on a simple transformation of $\hat{\rho}_n$: an indicator for being efficiency-focused in the sense of having an estimated $\hat{\rho}_n \geq 0$ (such that the fraction of the budget spent on *other* decreases as the relative price of redistribution increases).[25] 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]

The full sample results in Table 7 columns (1)–(3) suggest a substantial 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

[24] Results including session-level controls available upon request. Point estimates are similar when session-level controls are included.

[25] We focus on this transformation because it allows us to estimate effects via OLS, cluster our standard errors at the session level, and implement the Wild cluster bootstrap procedures described above to adjust for the small number of sessions. In Online Table 3, we present quantile regressions in which $\hat{\rho}_n$ is the dependent variable; these alternative specifications generate similar results.

the inconsistent patterns across columns (4)–(9). This imprecision is partially explained by the reduction in sample size that results from screening out the most selfish subjects.

One concern is that results might be accounted for 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. This is hard to square with several patterns in the data: The high efficiency orientation in the two recession environments is driven in part by an increase in the 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.

5 Conclusion

Many complex social and economic behaviors invoke distributional preferences. In this paper, we study the relationship between macroeconomic circumstances and distributional preferences, an important consideration for understanding, for example, political support for taxation and redistribution over the business cycle. We conducted experiments measuring distributional preferences during the "Great Recession" and during the preceding economic boom. 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 simulates recessionary conditions within the laboratory amplifies these effects, bolstering our view that these shifts in distributional preferences may be attributed to the onset of the Great Recession.

Our study also contributes to the debate over the role of experimental research in understanding individual preferences, as discussed in Levitt and List (2007), Falk and Heckman (2009), and Camerer (forthcoming). 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 experimental studies, particularly those measuring distributional preferences. Our results speak to this discussion by showing that exposure to recessionary conditions may directly impact individual distributional preferences. This correlation between behavior in laboratory experiments and circumstances in the real world suggests that such experiments capture something essential about the way individuals make decisions across a range of settings.

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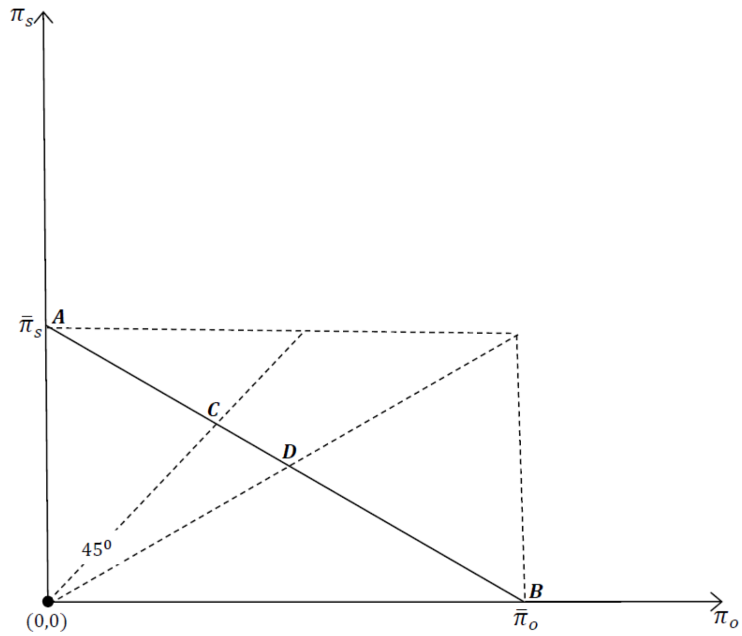
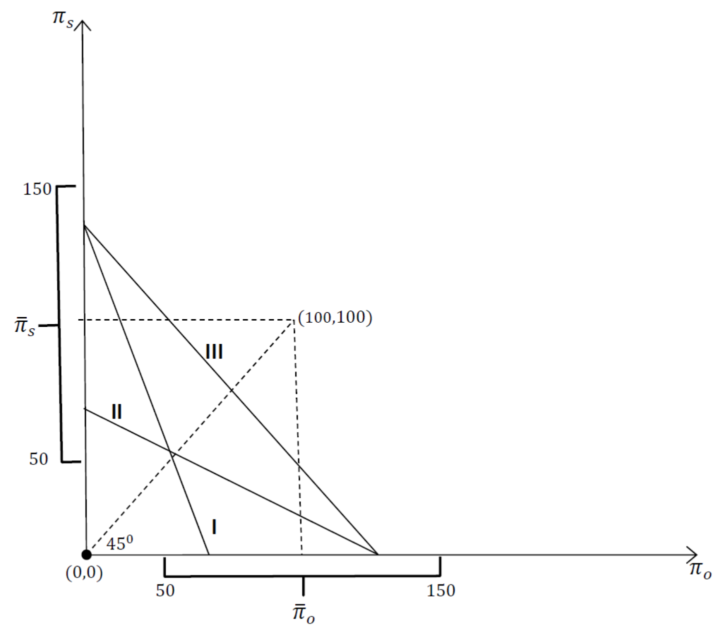
Figure 1: Experimental Design: Gain Treatment



The figure presents an example of a budget line that subjects faced in the GAIN treatment. $\bar{\pi}_s$ and $\bar{\pi}_o$ are the endpoints of the budget line, so we can calculate the relative price of redistribution, $p_s/p_o = \bar{\pi}_o/\bar{\pi}_s$. Selfish preferences $u_s(\pi_s, \pi_o) = \pi_s$ are consistent with allocation A, utilitarian preferences $u_s(\pi_s, \pi_o) = \pi_s + \pi_o$ are consistent with allocation B, and Rawlsian or maximin distributional preferences are consistent with allocation C which lies on the diagonal. Cobb-Douglas distributional preferences $u_s(\pi_s, \pi_o) = \pi_s \pi_o$ are consistent with allocation D which is the centroid of a budget line so that equal budget shares are spent on *self* and *other* $p_s \pi_s = p_o \pi_o$.

Figure 2: Experimental Design: Loss Treatment



The figure presents examples of budget lines that subjects faced in the LOSS treatment. $\bar{\pi}_s$ and $\bar{\pi}_o$ are the endpoints of the budget line, so we can calculate the relative price $p_s/p_o = \bar{\pi}_o/\bar{\pi}_s$. Numbers on the axes represent the sum of the initial endowment of $(100, 100)$ plus the payoff from the dictator game experiment. After the payoffs are rescaled by the initial endowment of $(100, 100)$, at least one of the endpoints of each budget line is above 100, but no endpoint is below 50 or above 150. Given the steep (flat) 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.

Figure 3: Job Offers Received by UC Berkeley Students at Graduation

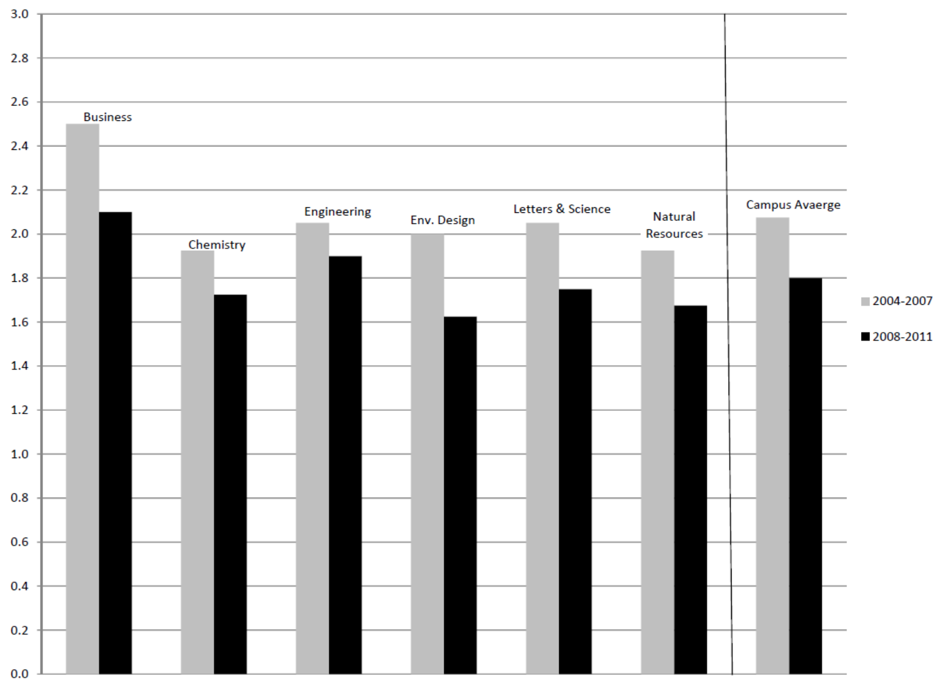


Figure 4: Employment Rate of UC Berkeley Students after Graduation

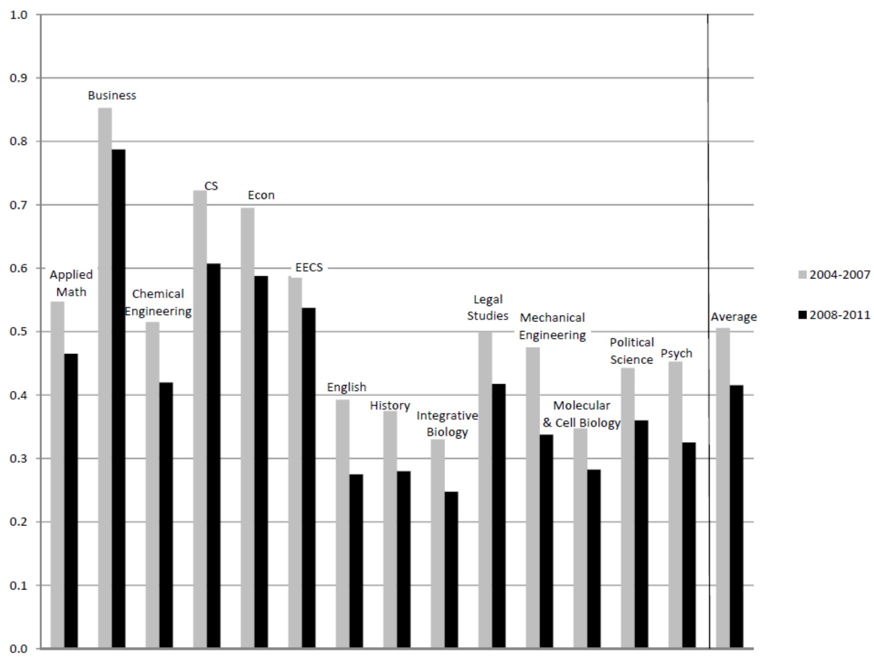


Figure 5: Real Growth of Starting Salaries for UC Berkeley Graduates

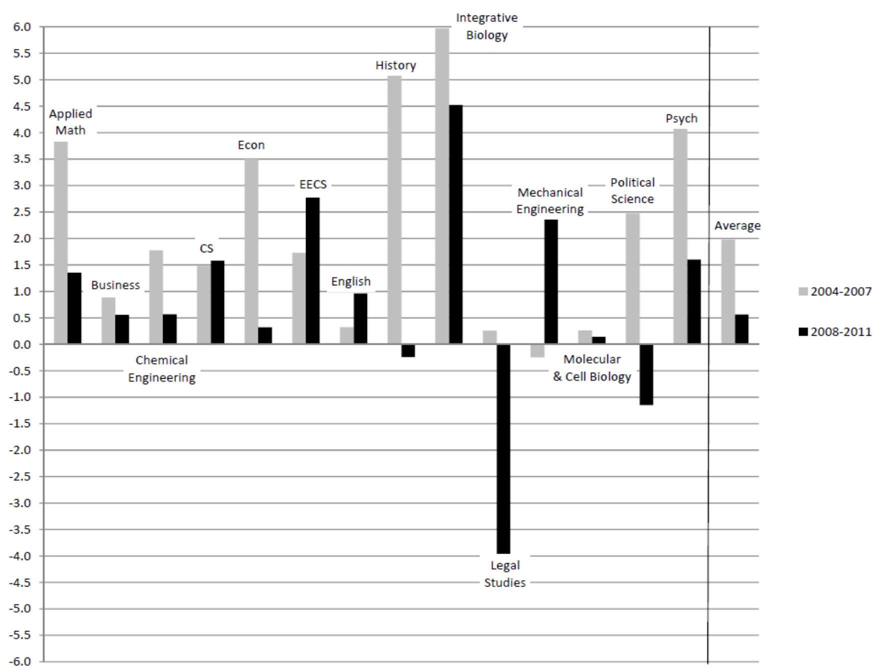
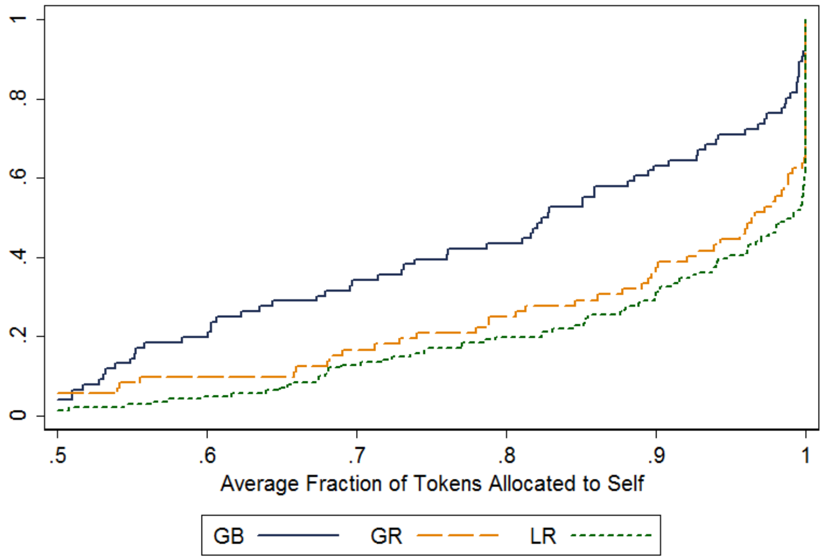


Figure 6: Empirical CDF of Average Fraction of Tokens to *Self*, $\pi_s/(\pi_s+\pi_o)$



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

Figure 7: Optimal Fraction of Tokens Allocated to *Self* by Log Price Ratio

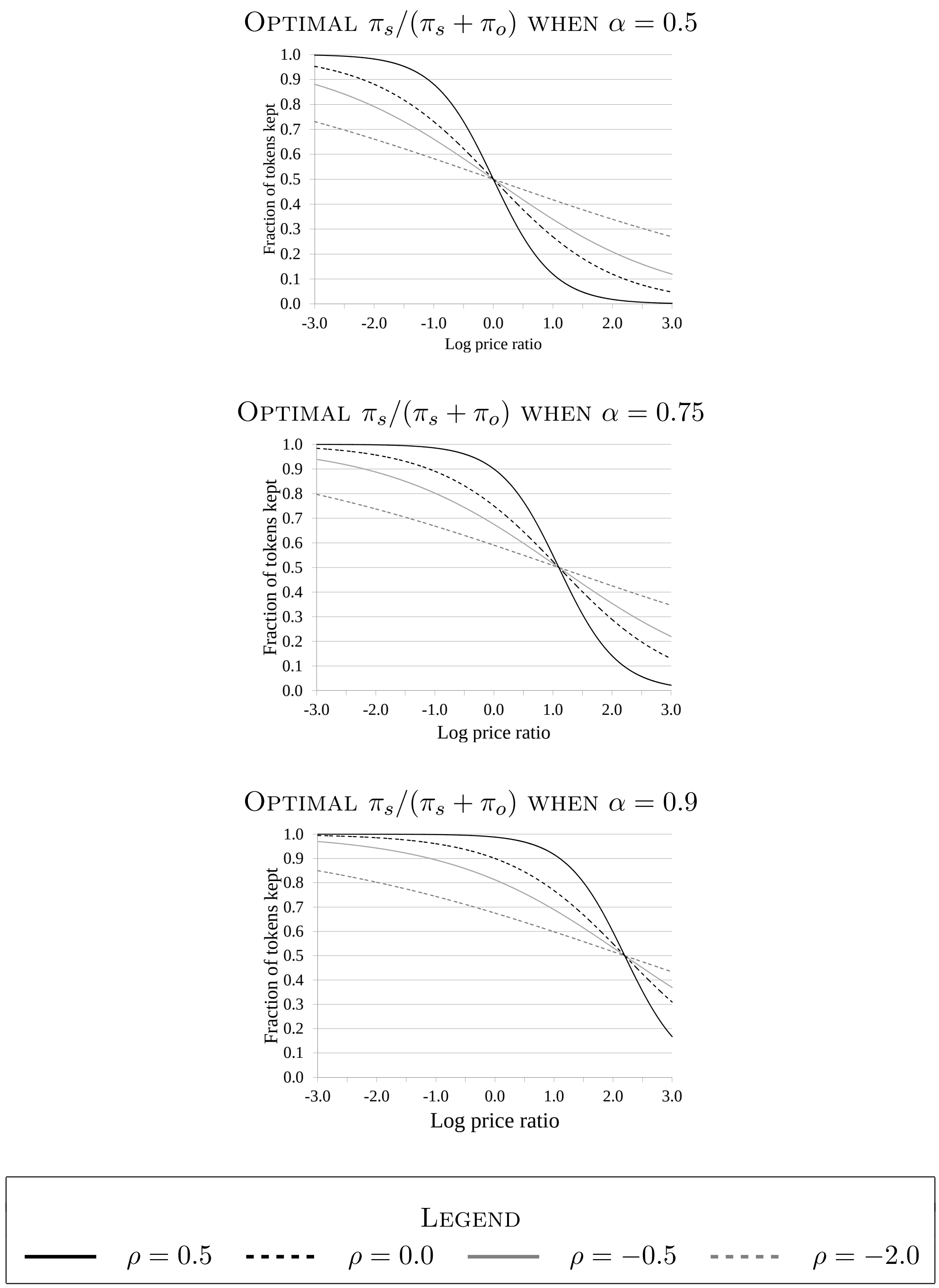
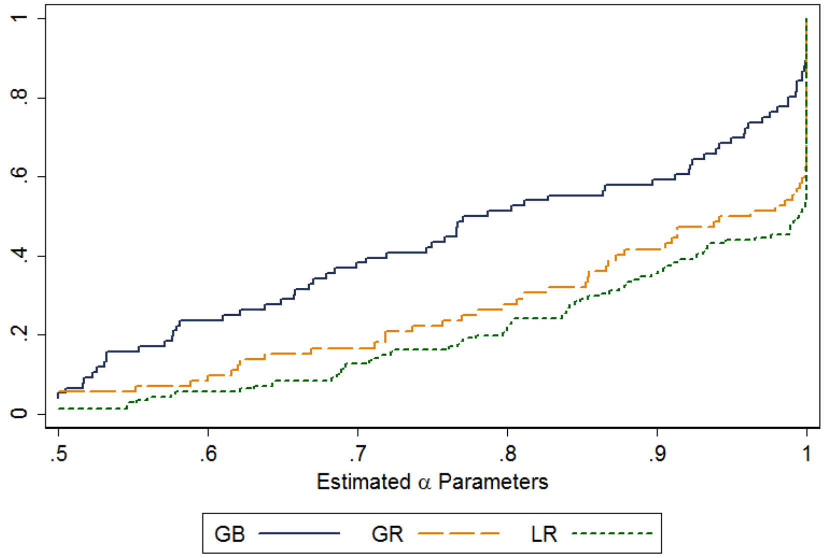
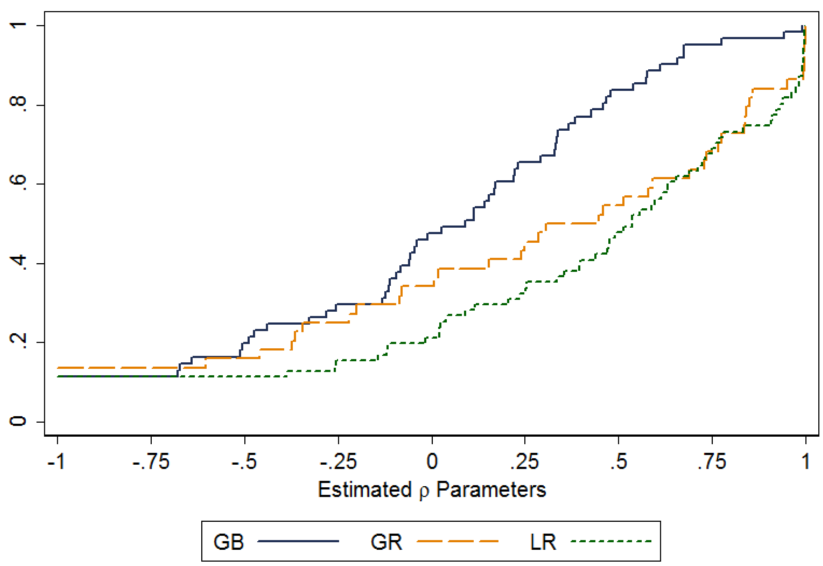


Figure 8: Empirical CDF of Estimated $\hat{\alpha}_n$ Parameters



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

Figure 9: Empirical CDF of Estimated $\hat{\rho}_n$ Parameters



Note: 18 of 176 estimated 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

	Session	Date	Obs.	Distribution of $\pi_s/(\pi_s+\pi_o)$ 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)
Panel A: Without session-level controls									
Recession	0.104***	.	0.081***	0.118***	.	0.09***	0.13***	.	0.102***
	(0.012)		(0.01)	(0.018)		(0.015)	(0.02)		(0.018)
Loss	.	0.076***	0.034***	.	0.088***	0.044***	.	0.091***	0.044***
		(0.021)	(0.006)		(0.024)	(0.01)		(0.028)	(0.015)
Constant	0.793***	0.832***	0.793***	0.798***	0.844***	0.798***	0.804***	0.858***	0.804***
	(0.009)	(0.02)	(0.009)	(0.014)	(0.023)	(0.014)	(0.015)	(0.026)	(0.015)
Session-level-controls	No	No	No	No	No	No	No	No	No
Recession p-values	0.004	·	0.002	0.004	·	0.063	0.008	·	0.002
Loss p-values	·	0.012	0.016	·	0.01	0.063	·	0.012	0.063
Observations	289	289	289	258	258	258	225	225	225
R^2	0.073	0.05	0.08	0.101	0.074	0.114	0.124	0.085	0.138
Panel B: Including session-level controls									
Recession	0.1***	.	0.076***	0.125***	.	0.075***	0.145***	.	0.081***
	(0.011)		(0.003)	(0.022)		(0.002)	(0.029)		(0.001)
Loss	.	0.105***	0.038***	.	0.147***	0.08***	.	0.179***	0.107***
		(0.012)	(0.003)		(0.015)	(0.004)		(0.015)	(0.001)
Constant	0.591***	0.598***	0.586***	0.567***	0.562***	0.556***	0.579***	0.546***	0.543***
	(0.049)	(0.126)	(0.013)	(0.109)	(0.121)	(0.022)	(0.136)	(0.132)	(0.007)
Session-level-controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recession p-values	0.029	·	0.123	0.061	·	0.104	0.07	·	0.025
Loss p-values	·	0.123	0.068	·	0.119	0.049	·	0.117	0.02
Observations	289	289	289	258	258	258	225	225	225
R^2	0.082	0.073	0.084	0.114	0.111	0.123	0.138	0.141	0.156

Robust standard errors clustered at the session level. "Loss p-values" and "Recession p-values" rows report bootstrapped p-values which correct for the small number of clusters following the procedures describe in Cameron, Gelbach, and Miller (2008) and Cameron and Miller (2015). OLS specifications reported. *, **, *** 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 ≥ 0.8			CCEI ≥ 0.9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recession	0.105***	.	0.08***	0.111***	.	0.079***	0.126***	.	0.098***
	(0.014)		(0.009)	(0.019)		(0.017)	(0.021)		(0.019)
Loss	.	0.079***	0.038***	.	0.088***	0.049***	.	0.089***	0.043**
		(0.023)	(0.011)		(0.025)	(0.016)		(0.03)	(0.018)
Constant	0.782***	0.821***	0.782***	0.792***	0.832***	0.792***	0.793***	0.845***	0.793***
	(0.009)	(0.02)	(0.009)	(0.014)	(0.021)	(0.014)	(0.016)	(0.025)	(0.016)
Recession p-values	0.008	·	0.063	0.016	·	0.031	0.012	·	0.031
Loss p-values	·	0.008	0.125	·	0.008	0.063	·	0.016	0.094
Observations	289	289	289	258	258	258	225	225	225
R^2	0.071	0.052	0.079	0.084	0.07	0.098	0.11	0.076	0.123

Robust standard errors clustered at the session level. "Loss p-values" and "Recession p-values" rows report bootstrapped p-values which correct for the small number of clusters following the procedures describe in Cameron, Gelbach, and Miller (2008) and Cameron and Miller (2015). OLS specifications reported. *, **, *** indicate 10, 5, 1 percent significance levels, respectively.

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

Dependent Variable: Indicator for Efficiency Focus (Estimated $\hat{\rho}_n \geq 0$)

Sample:	All Subjects			CCEI $\geq$ 0.8			CCEI $\geq$ 0.9		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Recession	0.215***	.	0.135***	0.157**	.	0.061	0.115*	.	-0.033
	(0.064)		(0.049)	(0.067)		(0.058)	(0.068)		(0.041)
Loss	.	0.208***	0.13**	.	0.197***	0.163***	.	0.241***	0.259***
		(0.068)	(0.056)		(0.05)	(0.049)		(0.027)	(0.033)
Constant	0.525***	0.581***	0.525***	0.58***	0.607***	0.58***	0.658***	0.643***	0.658***
	(0.045)	(0.043)	(0.045)	(0.048)	(0.034)	(0.048)	(0.028)	(0.022)	(0.028)
Recession p-values	0.027	·	0.063	0.078	·	0.438	0.152	·	0.563
Loss p-values	·	0.035	0.125	·	0.016	0.063	·	0.004	0.002
Observations	176	176	176	145	145	145	113	113	113
R^2	0.047	0.047	0.058	0.026	0.042	0.045	0.015	0.07	0.071

Robust standard errors clustered at the session level. “Loss p-values” and “Recession p-values” rows report bootstrapped p-values which correct for the small number of clusters following the procedures describe in Cameron, Gelbach, and Miller (2008) and Cameron and Miller (2015). OLS specifications reported. *, **, *** indicate 10, 5, 1 percent significance levels, respectively.