Intergenerational Advice and Matching: An Experimental Study *

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Abstract

This paper is motivated by the idea that economic mechanisms should be tested in the environments in which they are used in the real world. For example, in school matching parents whose children are currently in the match receive advice from their predecessors. We investigate the impact of this intergenerational advice and demonstrate that it is dramatic. We find that while subjects who repeatedly play the Gale-Shapley mechanism for 20 rounds wind up reporting truthfully 77% of the time, those who play the game once and get advice from their predecessors, wind up reporting truthfully only 44% of the time. We offer an explanation for this result that contrasts the experiential learning that takes place in our repeated treatments with the social learning that takes place in our intergenerational treatments.

Key Words: School Choice, Matching, Mechanism Design, Intergenerational Advice, Reinforcement Learning Model

JEL Classification: C78, C91, C72

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1 Introduction

Economic mechanisms, once in place, tend to have a life of their own. Once a mechanism (like a school-matching mechanism) is in place it tends to be used by a series of agents who use the mechanism for a while and are then replaced by later generations of agents who do likewise. For example, in school matching each year one cohort of parents engage in a match only to be replaced by another generation in the succeeding year. Intergenerational advice is passed on from one year or generation to the next so that how the time-t generation behaves is, in part, a function of the conventional wisdom they inherit from their predecessors.[1] If the agents learn to behave in accordance with the equilibrium predictions of the static theory, then that advice will be passed down and observed behavior will be consistent with the theory. However, because people have limited contact with the mechanism (most parents engage in it once or perhaps twice) what is learned and passed on need not be consistent with the predictions of the theory (or even represent a best response to previous experience). It is in this sense that mechanisms may take on a life of their own independent of the underlying theory.

In this paper we make a simple comparison. We run two school matching mechanisms, the Gale-Shapley Deferred-Acceptance mechanism and the Boston mechanism, under two different treatments. In one treatment groups of 5 subjects engage in a matching mechanism where three different types of objects are being allocated and do so for 20 rounds with random matching after each round. In other words, subjects are allowed to repeat playing with the mechanisms 20 times and presumably are able to learn how best to behave. In a second treatment with different subjects, 20 independent generations of subjects engage in the matching mechanism once and only once but pass on advice to their successor after each generation as to how to behave. In these treatments the only source of learning is via intergenerational advice so how subjects behave depends, in part, on what the conventional wisdom passed down generation by generation. (Each generation has incentives to pass on payoff-maximizing advice since each subject in a generation gets a payoff equal to what he earns during his lifetime plus 1/2 of what his successor earns.)

We find that, when the Gale-Shapley mechanism is used, the evolution of behavior is very different when we compare the time path of play across our two treatments. For example, when the same subjects repeatedly play in the Gale-Shapley mechanism (a mechanism where truth-telling is a dominant strategy) the fraction of subjects who report

[1] In Ding and Schotter (2014) we make a distinction between advice that flows between contemporaneous parents in a school matching program during the year their children are involved (what we call horizontal advice) and advice passed down from pervious generations of parents who have used the mechanism in the past (what we call vertical advice). This paper concentrates on vertical advice while Ding and Schotter (2014) focuses on horizontal advice via social networks.

truthful strategies increases monotonically over time so that in the last five rounds 77.14% of subjects report the truth compared to 64.57% in the first five rounds. Surprisingly, the opposite is true in our intergenerational Gale-Shapley treatment where the fraction of subjects telling the truth falls from 72.00% in the first five rounds to 44.00% in the last five rounds.[2] This difference is significant because outside the lab, when a school choice mechanism is used, it is more likely to be used in a setting where advice is passed on in an intergenerational manner rather than where people engage in the mechanism repeatedly over their lifetime. As we have mentioned, typically people use a school matching mechanism once or twice in their life but then advise their friends who succeed them as to how to behave. If either result is likely to be externally valid it is probably the intergenerational result since that treatment most closely mimics the environment where such mechanisms are used.

Ironically, as time progresses, the efficiency achieved by subjects in the intergenerational Gale-Shapley treatment approaches 96.67% which is significantly greater than that achieved by subjects in both the repeated Gale-Shapley treatment and two of the Boston treatments. In other words, while subjects in the intergenerational Gale-Shapley treatment do not learn their dominant strategy, they still outperform their cohorts in the repeated Gale-Shapley treatment. (The Gale-Shapley mechanism, while determining stable outcomes, does not guarantee efficient outcomes.)

When the Boston Mechanism is used there exists no statistically significant difference between our repeated and intergenerational treatments. The fraction of subjects reporting the truth in the first five rounds (generations) are 56.00% and 48.00% in the repeated and intergenerational treatments, respectively, while in the last five rounds (generations) those percentages are 62.00% and 72.00%, respectively. The fraction of truth-telling increases in both treatments, and there is no statistically significant divergence in behavior across these treatments.

The lesson learned by these results is similar to that of Ding and Schotter (2014) (where advice was passed on between contemporaneous subjects via social networks rather than intergenerationally), and is that, when one tries to test the performance of a matching (or other) mechanism, one must be careful to test it in the environment similar to the one where the mechanism functions in the real world rather than the one envisioned by theory. In our experiments we consider the relevant behavior of subjects to be that behavior displayed by our subjects at the end (last five or ten rounds) of their generational participation rather than either their first round behavior or that behavior observed after 20 rounds of repeated play. What happens to mechanisms in the real world

[2]For the Boston mechanism, over time, the fraction of subjects reporting truthfully in both the repeated and intergenerational treatments converge.

is that after they are used participants in the mechanism develop a sense of conventional play and that play gets transmitted across generations. While the wisdom passed down may vary across different groups of people who use the mechanism, the object of interest is the convention created which may be very different from what subjects might learn by themselves after enough experience. As in Schotter and Sopher (2003, 2006, 2007) where a similar intergenerational structure is used, what we observe in intergenerational games is a type of punctuated equilibrium where a convention of behavior is established, passed along to succeeding generations only to be disrupted by some later generation whereupon a new convention is created.

Because our intergenerational experimental results are based on only one time series each for our Boston and Gale-Shapley treatments (albeit generated by the behavior of 100 largely independent subjects in each treatment), later in the paper we present two learning models describing behavior in each of our treatments, estimate them structurally, and then use the resulting parameter estimates to simulate behavior in each of our four treatments. We find that while the qualitative behavior across treatments remains intact, with the repeated Gale-Shapley mechanism exhibiting the most truth-telling behavior of all treatments and significantly more than the intergenerational Gale-Shapley mechanism, the fraction of subjects predicted to tell the truth is higher in the simulation than in our experiment.

In the remainder of this paper we proceed as follows. In Section 2 we describe our experimental design, while in Section 3 we present our results. Section 4 provides an explanation our results while in Section 5 we formalize this explanation by presenting two reinforcement-learning models, estimate them structurally, and then use the estimated parameters in a simulation. Section 6 discusses advice giving and advice following. Section 7 offers a short literature review. Finally, Section 8 presents our conclusions.

2 Experimental Design

All our experiments were conducted in the experimental laboratory of the Center for Experimental Social Science at New York University. Two hundred seventy-five students were recruited from the general undergraduate population of the university using the CESS recruitment software. The experiment was programmed using the z-tree programming software (Fischbacher (2007)). The typical experiment lasted about an hour with average earnings of \$25.19. Subjects were paid in an experimental currency called Experimental Currency Units (ECU's) and these units were converted into U.S. dollars at a rate specified in the instructions. To standardize the presentation of the instructions, instead of reading the instructions, after the students had looked the instructions over, we showed a pre-recorded video which read them out load and simultaneously projected the written text on a screen in front of the room. The video for one treatment can be downloaded at https://files.nyu.edu/td648/public/IntergenerationalAdvice/, while the printed instructions are available in Appendix A.

The experiment run had four treatments which differed according to whether the subjects used the Boston or the Gale-Shapley Deferred Acceptance mechanisms and by whether they were allowed to repeat the experiment 20 times, with random matching between each round, or whether they could perform the experiment only once and then pass on advice to subjects who replaced them in the mechanism. In the intergenerational treatments, subjects received a payoff equal to the payoff they received during their one-period lifetime as well as a sum equal to 1/2 of the payoff of their immediate successors. This ensured that they were incentivized to pass of payoff maximizing advice.

In any session of our treatments we recruit 20 subjects (some sessions had fewer due to lack of attendance) and when they arrive in the lab we randomly allocate them to groups of five designated Type 1, Type 2, Type 3, Type 4 and Type 5. Hence, in any given session there were four subjects of each type. Within each group there are 5 objects grouped into three types which are called Object A, Object B, and Object C. In total there are 2 units of Object A, 2 units of Object B and 1 unit of Object C.

Preferences were then induced on the subjects by informing each of them about their ordinal preference over objects (see Table 1) and the fact that subjects would receive \$24 if they are allocated their first-best object, \$16 if they receive their second-best, and \$4 if they receive their third-best.

Table 1 presents the full preference matrix of our subject types. These preferences are the same for all our experimental sessions.

Table 1: Preferences over Schools

	Student Preferences				
Type	1	2	3	4	5
1^{st} choice	C	C	C	A	A
2^{nd}choice	A	A	B	B	C
3^{rd}choice	B	B	A	C	B

In the experiment subjects are matched to objects using one of two different matching mechanisms, the Boston or the Gale-Shapley mechanisms. This is done by having each subject enter a ranking of the objects as an input to the mechanism algorithm and then allowing the algorithm to do the matching.

In addition to the preferences each subject is endowed with, some are also endowed with a priority in the allocation of certain objects. In all treatments, it is common knowledge that Types 1 and 2 are given priority for Object A, while Type 3 is given priority for Object B and Types 4 and 5 are not given priority for any objects. When the number of subjects of equal priority applying for an object is greater than the number of objects available, the algorithm employs a lottery to break ties.[3] Note that Types 1 and 2 are identical with respect to both their preferences and priorities.

Subjects are told their own types and matching payoffs for each object as well as a priority table, but they do not know the types or the object payoffs of any subjects other than themselves. They are then required to state their rankings over objects. Based on the information subjects provide, one of the matching algorithms (either the Boston or the Gale-Shapley mechanism) determines the allocation outcome. Each subject is matched to one and only one object. All parameters, preferences and priorities were identical to those used in Ding and Schotter (2014) high preference intensity treatments where advice was offered between contemporaneous subjects via social networks rather than intergenerationally.

The two mechanisms used can be described as follows:

2.1 Boston Mechanism

Step 1) Only the first choices of the students are considered. For each school, consider the students who have listed it as their first choice, and assign the seats in the school to these students one at a time following the school's priority order until either there are no seats left or there are no students left who have listed it as their first choice.

In general, at

Step k) Consider the remaining students. Only the kth choices of these students are considered. For each school with still available seats, consider the students who have listed it as their kth choice, and assign the remaining seats to these students one at a time according to priority until either there are no seats left or there are no students left who have listed it as their kth choice.

This mechanism, while widely used, is not strategy-proof.

2.2 Gale-Shapley Deferred Acceptance Mechanism

Step 1) Each student proposes to her first choice. Each school tentatively assigns its seats to its proposers one at a time following its priority order until either there are no seats left or there are no students left who have listed it as their first choice.

In general, at

[3] In our experiment we used a single lottery instead of object specific lotteries to break ties.

Step k) Each student who was rejected in the previous step proposes to her next choice. Each school considers the students who has been held together with its new proposers, and tentatively assigns its seats to these students one at a time according to priority, until either there are no students left who have proposed or all seats are exhausted. In the latter case, any remaining proposers beyond the capacity are rejected. The algorithm terminates either when there are no new proposals, or when all rejected students have exhausted their preference lists.

The Gale-Shapley mechanism is strategy-proof regardless of information structures. Though it generally does not guarantee Pareto-optimal results, it does determine student-optimal stable matches when students and schools have strict preferences (see Dubins and Freedman (1981), and Roth (1982)), *i.e.*, no other stable assignment Pareto dominates the outcome produced by the Gale-Shapley mechanism, although this outcome might be Pareto dominated by some unstable assignments. In our experimental design we consider coarse priorities.

For each mechanism we run two treatments which we call the Repeated and the Intergenerational treatments. In the Repeated treatment subjects repeatedly engage in the matching mechanisms 20 times with random matching of subjects after each round. Subjects retain their type in each round. At the end of the experiment, one of the 20 rounds is drawn for payment. In the intergenerational experiment, after subjects are allocated into groups of five and given a type, each group is randomly assigned a number from 1 to 4. Subjects in Group 1 will play the matching game first. After they finish, they are replaced by subjects of their own types in Group 2 (their successors) who then engage in an identical decision problem among themselves. Similarly, after the participation of Group 2 subjects is over, they will be replaced by Group 3, and Group 3 will be replaced by Group 4. Group 4 subjects will be replaced by Group 5 subjects, but since we only recruit 20 subjects, their successors will be the first group in the next experimental session. Hence, the experiment extends beyond the session being run. In both the treatments, after each round (generation) subjects are informed only about their own outcomes and payoffs.

After a subject is done with his part in the experiment, and knows the outcome of his match, he is asked to give advice to that subject in the next group who will be his successor. Each subject has a successor of his own type so subjects of type 1 give advice to successors of type 1, and the same for types 2 to 5. The advice given is of two forms. First, the subject actually enters a preference ranking into the advice box which is the preference ranking he suggests that his successor uses. In addition, subjects are allowed to write a free-form message to explain the rationale behind this suggestion. Hence, except for the first generation, each generation is presented with advice before they enter their preference. The payoff of a subject is equal to the payoff they receive for his match plus an amount equal to 1/2 of the payoff of his successor. When all four groups in a session are done, each is paid for their participant with the last group told that they would receive the second portion of their payoff after the next session is run and we know the payoff of each subject's successor. When the 20^{th} generation was done, since there were no successors, all subjects were told that there will not be another session run and each is given a payoff equal to 1/2 of the mean payoff of the the 20^{th} generation. Note that in this design we generate one time series of length 20 with each generation consisting of 5 subjects playing the matching game so that in total there were 100 subjects engaging in each intergenerational experiment.

Table 2 describes our experimental design:

Table 2: Experimental Design

Treatment	Learning Mode	Mechanism	# of Rounds (Gen.)	# of Sessions	# of Subjects
1	Repeated	Boston	20	2	40
2	Intergenerational	Boston	20	6	100
3	Repeated	Gale-Shapley	20	2	35
4	Intergenerational	Gale-Shapley	20)	8	100
				Total:18	Total: 275

3 Results

The main result of our experiment is that there is a qualitative and quantitative difference in the way subjects behave in our intergenerational and repeated treatments, when the Gale-Shapley mechanism is used but not so when our subjects used the Boston mechanism. More precisely, despite the fact that truth-telling is a dominant strategy in the Gale-Shapley mechanism, the fraction of subjects who report truthfully decreases monotonically over time in the Gale-Shapley intergenerational treatment where subjects wind up submitting significantly fewer truthful preferences in the last five generations of their interaction than do subjects in the last five generations or rounds of any of our other three treatments. However, the opposite is true when the Gale-Shapley mechanism is played repeatedly, since there the fraction of subjects reporting truthful preferences increases monotonically over generations and in the last five generations subjects wind up submitting significantly more truthful preferences than any of our other three treatments. This means that subjects learn very different lessons when the Gale-Shapely mechanism is played in a finitely repeated manner as opposed to intergenerationally.

This divergence is not seen when the Boston mechanism is used since the fraction of subjects reporting truthfully in the Boston Repeated and Boston Intergenerational treatments are similar during both the first and last five rounds.

Despite their failure to report truthful preferences, however, subjects in the last five generations of the intergenerational Gale-Shapley experiment capture a higher percentage of the first-best allocation payoffs than do subjects in any of the other three treatments.

In the remainder of this section we will first present some descriptive evidence in support of our main results and then turn our attention to offering an explanation.

Figure 1: Fraction of Truth-telling in All Treatment

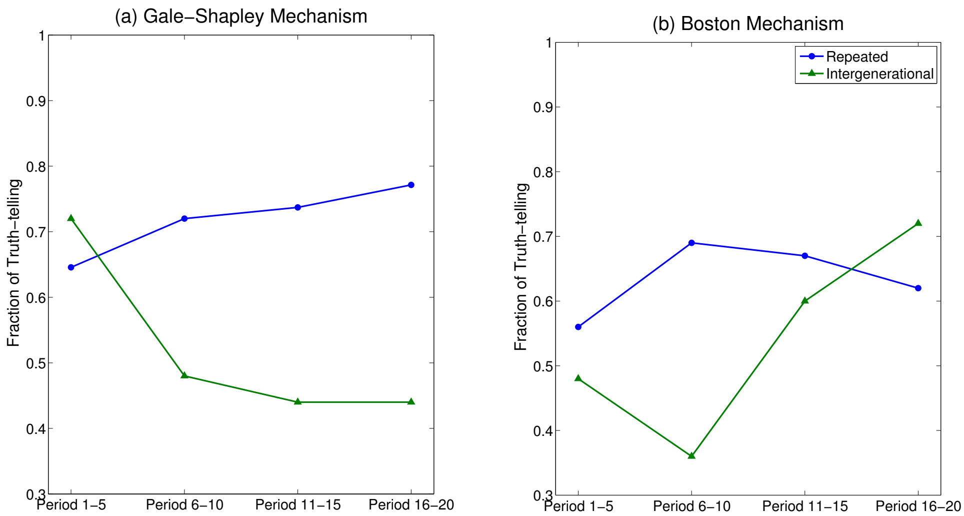


Figure 1 (a) shows the fraction of subjects reporting truthful preferences over the 20 rounds (generations) of the repeated (intergenerational) Gale-Shapley treatments, while Figure 1(b) shows the same fraction for the Boston mechanism. Here rounds (generations) are placed on the horizontal axis and the fraction of subjects submitting truthful preferences on the vertical axis. Rounds or generations are aggregated into four bins aggregating behavior in rounds (generations) 1-5, 6-10, 11-15 and 16-20.[4]

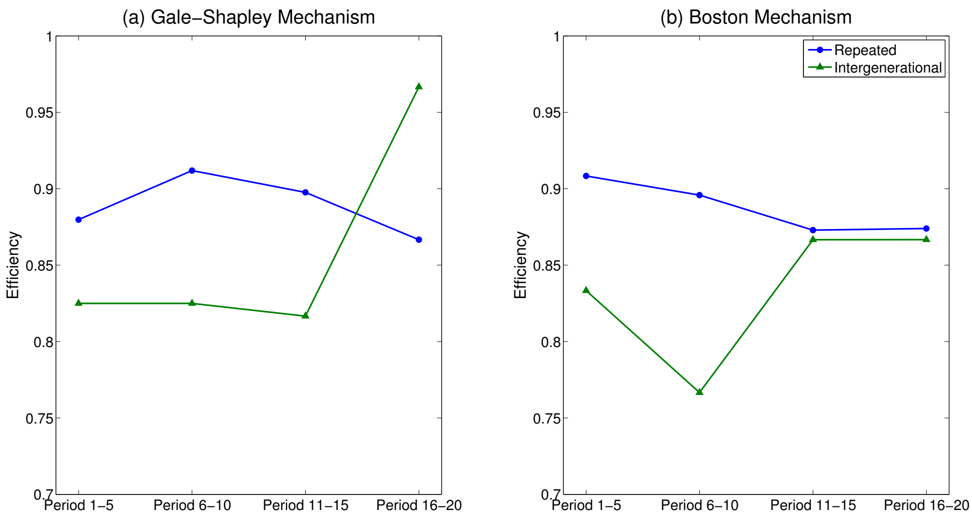
What is striking is how the fraction of subjects who report the truth in the Gale-Shapley intergenerational treatment monotonically decreases from the first five to last five generations while it monotonically increases in the repeated Gale-Shapley mechanism treatment. More precisely, while the fraction of subjects reporting truthful preferences in the repeated Gale-Shapley treatment increases from 0.6457 to 0.7714 (difference significant at $p < 0.001$) over the 20 rounds of the experiment, the faction reporting truthful preferences in the Gale-Shapley intergenerational treatment decreases from 0.72 to 0.44 (difference significant at $p < 0.0696$), a very dramatic change.

[4]Note that while in our repeated game experiments we are aggregating over groups of five subjects every five rounds, in our generation experiments, since we only have one time series, in each five-generation interval we are aggregating over five different generation each containing five subjects.

No such difference exists when we look at the Boston mechanisms and compare behavior in the 20 round repeated and 20 generation intergenerational treatments. Here, while truth-telling increases over the 20 rounds (generations) from 0.56 to 0.62 in the repeated Boston treatment and from 0.48 to 0.72 in the Boston intergenerational treatment, there is no difference between the fraction of subjects who report truthfully across the last five rounds and generations of these treatments ($p < 0.3149$).

Figure 2 (a) describes the fraction of the first-best efficiency that is captured by our Gale-Shapley mechanisms over time, while Figure 2 (b) presents the same fraction for the Boston mechanism. One immediately obvious feature of Figure 2 is that over time the efficiency of our inter-generational Gale-Shapley mechanism approaches 96.67% which is significantly higher than the 86.67% efficiency attained by the repeated Gale-Shapley mechanism ($p < 0.0360$) and the 87.40% and 86.67% captured in the intergenerational and repeated Boston treatment (significant different at $p < 0.8502$.)

Figure 2: Efficiency in All Treatment



Such differences were not found between the repeated and intergenerational play of our Boston mechanism during the last five rounds. This contrast is interesting because since it is a dominant strategy to report truthfully in the Gale-Shapley mechanism whether it is played repeatedly or via generations, one would think that behavior there would be similar.

4 Explaining our Results

From our description above it would appear that what needs to be explained is why truth-telling behavior diverged between the repeated and intergenerational Gale-Shapley treatments but not for the Boston treatments. In this section we provide one such explanation which relies on a distinction between experiential and social learning.

The main idea driving our explanation is the difference between the type of learning that takes place across our repeated and intergenerational treatments. As is true in most experiments, we do not expect subjects to reach the equilibrium of the game they are playing in the first round of play. Rather they learn it as the game is repeated. When the game they are playing has a dominant-strategy (truth-telling) equilibrium, we expect that over time our subjects would converge on such an equilibrium. In fact, if our subjects learn using a reinforcement learning rule, as we will assume later, then as Beggs (2005) demonstrates, they will in fact converge to an all-truthful equilibrium. This is our expectation for the repeated Gale-Shapley mechanism.

However, when the matching game is played as an intergenerational game, we no longer expect such convergent behavior since, as we will see below, each subject plays the game only once and is forced to make a decision on the basis of his interpretation of the instructions and the advice he receives. In such an environment, the result of Beggs (2005) is no longer relevant and we should not expect the same type of convergence to truth-telling even when all subjects have dominant strategies. This is true because the lack of experience with the game and the stochasticity of advice and choice will introduce a large volatility in behavior which will disrupt convergence. Since volatility is destructive of convergence, the more volatility one observes the less likely we are to experience a truth-telling equilibrium. As a result, if we can document that there is more volatility in behavior in the Gale-Shapley intergenerational treatment than in the Gale-Shapley repeated treatment, we will go a long way in explaining the divergence we observe across these treatments.

While our discussion above explains why we experienced a divergence in behavior between our Gale-Shapley repeated and intergenerational treatments, it does not explain why we failed to observe this divergence when the Boston mechanism was used since there, the fractions of subjects reporting truthfully in the last five rounds (generations) of the repeated and intergenerational treatments were not significantly different. The answer here is simple. In our experiment all mechanisms are performed by providing the subjects with limited information. While they knew their own preferences and priority, they were given very scant information about the constellation of preferences they faced. As such, they were not given enough information to construct the (full information) equilibrium and hence, unlike the Gale-Shapley treatments, where truth-telling is dominant, it was not clear in the Boston treatments what strategy was beneficial. In such an informationally sparse environment, it is not easy for our subjects to learn that any particular strategy is optimal. Hence, unlike the Gale-Shapley mechanism, where there was a dominant strategy that could be discovered, there was no particular advantage to playing the game repeatedly when the Boston mechanism was used. As a result, despite the increased volatility of behavior in our Boston-intergenerational treatment, the truth-telling behavior of our subjects across the two Boston mechanisms treatments ended up, over the last five rounds (generations), to be insignificantly different.

To support our explanation we will proceed as follows. First we will repeat our argument in more detail below. We will then present two reinforcement learning models, one for the repeated treatment and one for the intergenerational treatment, and estimate their parameters using maximum likelihood. Using these parameter estimates we then simulate the behavior in each of our four treatments and investigate whether the stylized facts generated by our experiment are replicated in our simulation. If our simulations in the Gale-Shapley intergenerational treatment exhibit more volatility than they do in the repeated treatment, then that will be an indicator that we should expect to see less convergence toward truth-telling in the intergenerational as opposed to the repeated treatment. While we also expect to see more volatility in the intergenerational Boston treatment than in the repeated Boston treatment, we do not expect to see a difference in the fraction of subjects reporting truthfully since we do not expect subjects in the repeated Boston treatment to converge toward full truth-telling.

4.1 Social versus Experiential Learning

The main difference between behavior in repeated and intergenerational environments centers around the type of learning that subjects engage in. In the repeated treatments learning, if it takes place, is experiential while in the intergenerational treatments it is social. More precisely, in a repeated game treatment, even if there is random matching after each round, a subject might be expected to learn experientially and gather experience over time. This can be done by experimenting with different preference-reporting strategies and altering one's behavior given the reinforcement provided by the feedback of the mechanism. Such learning may take many forms and might be captured by a reinforcement (Erev and Roth, 1998) or experience weighted attraction (Camerer and Ho, 1999) type of model.[5]

In the intergenerational treatments learning is primarily social with each subject engaging in the experiment only once and making their choice on the basis of their understanding of the instructions and on the advice they receive.

The main difference between experiential learning and social learning is that in the

[5]A reinforcement model may be preferable here since, given the lack of information our subjects experience it would be hard for them to calculate the counter-factual payoffs needed to use an EWA model.

repeated treatments subjects arrive in the lab, read the instructions, form some initial attraction to their various preference strategies, and then, as time goes on, update these attractions and, hence their actions, as they receive feed back.[6] If the feedback they receive is not compelling enough to lead them to change their behavior, then we might expect them to converge and not change their submitted preference since, strategies not used will fail to be reinforced and tend to disappear. Equilibrium, or at least stable behavior, occurs when no subject in the experiment feels it is worthwhile changing his behavior (or experimenting) given what they have observed in the past and their counter-factual beliefs about strategies not chosen. (See Fudenberg and Levine (1993) notion of self-confirming equilibrium).

In our intergenerational treatments, the process is different. Here, each subject arrives in the lab, reads the instructions and forms their own initial attractions to strategies just as subjects in the repeated treatments did before the first round. The difference here is rather than keep on playing the matching game and updating their attractions, subjects play only once in light of the advice received from their immediate predecessors and offer advice to their successors. When the next generation arrives, however, they play the matching game without any accumulated experience but simply with their initial attractions to strategies updated by the advice they receive. In other words, in the intergenerational treatments the game is played by a sequence of relatively naive subjects who only update their attractions to strategies once on the basis of the advice they receive. In such circumstances we should expect that behavior might be more volatile since, even if behavior has stabilized and each generational type is submitting the same preferences, there is always the likelihood that a newly arrived subject may ignore the advice he receives and upset the established convention. As in Celen et al. (2010), since, subjects do not know the history of play before they arrive, they have no way of knowing whether the advice they are receiving is about behavior that has been in place for a long time.

In the intergenerational social-learning treatments, as in Schotter and Sopher (2003), we might experience what is called "punctuated equilibria" where the behavior of subjects stabilizes for a while but then, as new subjects arrive, this behavior is destabilized. This occurs by one of three routes: (1) since choice is stochastic, there is always a chance that, no matter what he is advised, a subject will deviate from previous behavior; (2) a current subject may receive a bad payoff and, as a result, suggest to his successor that he should deviate, or (3) a newly arrived subject consciously refuses to follow the advice he receives. Hence, for these reasons we expect more stable behavior in the repeated treatments than in the intergenerational ones and hence, in the last five or ten rounds (generations) it is

[6]In the model we construct later in this paper, the probability of choosing any given strategy is a logit function of that strategy's attraction.

more likely to observe a broader variety of behaviors in the intergenerational treatments.

This distinction between experiential and social learning has some testable implications for our experiments. Since subjects in our repeated treatments start out with one vector of attractions to strategies and update it as information accumulates, it is possible that such subjects might eventually converge and their behavior stabilizes. If truth-telling is a dominant action as in the Gale-Shapley mechanism, then as Beggs (2005) has demonstrated, we would expect convergence to truth-telling. When the Gale-Shapley mechanism is played intergenerationally, however, we expect no such convergence and hence less truth-telling.

When a mechanism like the Boston mechanism is used in circumstances where it is impossible to calculate its equilibrium, experience is less valuable and we might expect less of a difference between our repeated and intergenerational treatments.

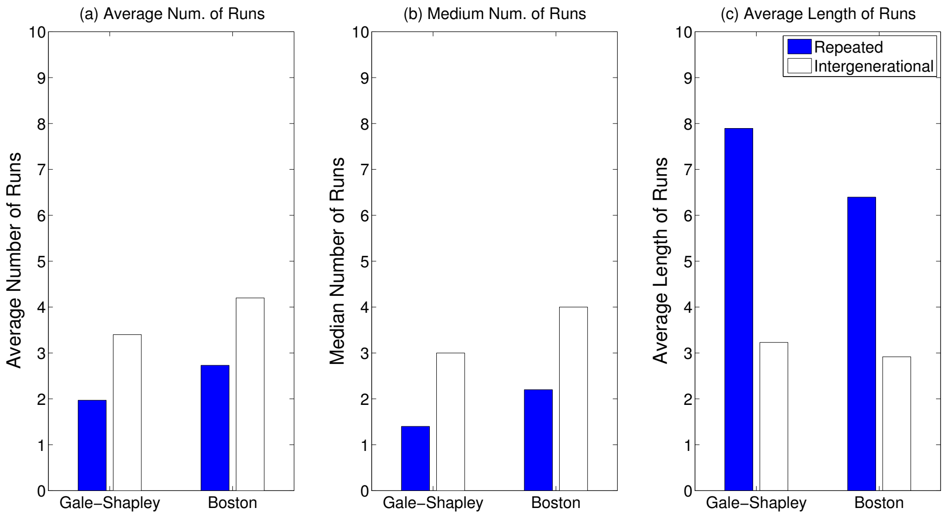
Our discussion above implies that we should observe less volatile behavior in the repeated game treatments over the last 10 rounds of the experiment than in the intergenerational games. By less volatility we mean fewer changes in the strategies submitted by the subjects over the last 10 round (generation) history and longer runs of identical behavior. More precisely, we will categorize a sequence A of choices made either by a single subject over time or a sequence of generational subjects as more volatile than sequence B if it involves more runs of identical choices of shorter average length than those of sequence B.

Figure 3 indicates that behavior was indeed more volatile in our intergenerational as opposed to our repeated treatments. It presents, for each treatment, the average and median number of runs as well as the average run length of runs over the last 10 rounds (generations) of the experiment. [7]

As we can see, no matter which matching mechanism is used, behavior appears to be more volatile in the intergenerational as opposed to the repeated treatments. For example, in the Gale-Shapley treatment, there are fewer runs of strategies (and hence fewer changes in behavior) in the last 10 rounds of the repeated treatment (1.97 on average) than there are in the last 10 generations of the intergenerational treatment (3.4) with each run being of longer duration (7.89 rounds versus 3.23 generations). Similar results hold for the Boston mechanism where there were, on average, 2.73 runs over the last 10 rounds of the repeated Boston mechanism treatment compared to 4.2 runs when we look at our intergenerational treatment with average lengths of 6.40 and 2.92 respectively. As a result, we are less likely to see convergence to one particular strategy (like truth-telling) in the intergenerational treatments than in the repeated treatments as we conjectured.

[7] These averages are taken over all subjects of any type in a given round or generation.

Figure 3: Volatility in Last 10 Rounds (Generations)



5 Structural Estimation and Simulation

Before we look at the results of our estimation exercise and simulations, let us pause to discuss the data that our experiment generates. In the repeated treatments we have a total of 75 subjects who function in groups of five over a 20 period horizon. There were 8 groups of 5 subjects in the Repeated Boston treatment and 7 groups of 5 in the Repeated Gale-Shapley treatment generating a total of 800 and 750 observations, respectively. In the intergenerational treatments we have 200 subjects (100 using each mechanism) who each engage in the experiment for one period and who collectively generate one 20-generation time series for the Boston and Gale-Shapley mechanisms. Hence, our intergenerational results are based on one and only one time series each.[8] Note, however, that the advice giving, advice following and choice behavior we observe in each intergenerational treatment is determined by 100 subjects making decisions in virtual isolation of each other (except for advice). To examine how robust our intergenerational time series results are we use our behavioral data to estimate two structural reinforcement learning models, one for the repeated and one for the intergenerational treatments, and use the parameter estimates to simulate what behavior would look like if we generated 10,000 time series for our 20-period experiment based on the estimated behavior generated in our structural estimation. We find that our experimental results are in line with our simulations but differ on some quantitative dimensions.

[8]The same was true of all papers using an intergenerational game design in Schotter and Sopher (2003, 2006, 2007); Chaudhuri et al. (2009); Nyarko et al. (2006) as well as national economic time series like interest rates, unemployment and GDP. In the case of macroeconomics, we are stuck with the one time series we have for each country and must make inferences from it alone.

5.1 Structural Estimation

As described above, there are two stylized facts that need to be explained. One is the fact that truth-telling behavior diverges across our repeated and intergenerational Gale-Shapley treatments does not in the Boston treatments. Second is the fact that the behavior of our subjects appears to be more volatile when they engage in an intergenerational treatment than when the game they are playing is repeated. In this subsection of the paper we will take a more formal approach to providing an explanation for these facts. More precisely, in this subsection we will present the results of two contrasting structural estimation exercises, one for our repeated-game treatments and one for our intergenerational treatment. We model both as reinforcement learning models which, for obvious reasons, differ due to the different environment in which they take place. We then use the parameter estimates derived from these structural estimation procedures in a simulation exercise to see if we can replicate what we see in the data with our simulation results.

We start with our repeated treatment where we use a simple, off-the-shelf reinforcement learning model. Say each subject i , after reading the instructions of our experiment, has an initial propensity to play his k^{th} pure strategy given by some nonnegative attraction number $A_i^k(0)$. If subject i plays his k^{th} pure strategy at time t and receives a payoff $\pi_i(s_i^k, s_{-i})$, at time $t+1$ his propensity to play strategy j is updated by setting

$$A_i^j(t) = \begin{cases} \phi A_i^j(t-1) + R_i^j & \text{if } j = k \\ \phi A_i^j(t-1) & \text{otherwise} \end{cases} \tag{1}$$

where $R_i^j = \pi_i(s_i^k, s_{-i}) - \min_j(\pi_i^j)$. Note that we normalize the reinforcement function by subtracting the minimal payoff.[9] ϕ is a decay rate which depreciates previous attractions. Choices are made using the exponential (logit) form to determine the possibility of observing s_i^j at time t :

$$P_i^j(t) = \frac{e^{\lambda \cdot A_i^j(t-1)}}{\sum_{k=1}^m e^{\lambda \cdot A_i^k(t-1)}} \tag{2}$$

For a given subject i, the likelihood function of observing a choice history of $\{s_i(1), s_i(2), ..., s_i(T)\}$ is given by

$$\prod_i^T P_i^{s_i(t)}(t|A(0), \lambda, \phi) \tag{3}$$

In our experiment T= 20. The joint likelihood function of observing all players' choice

[9]Similar normalization are done by Erev and Roth (1998)and Camerer and Ho (1999).

history is given by

$$L(A(0), \lambda, \phi) = \prod_{i}^{N} \Big\{ \prod_{i}^{T} P_i^{s_i(t)}(t|A(0), \lambda, \phi) \Big\}$$

The log likelihood is

$$LL(A(0), \lambda, \phi) = \sum_{t=1}^{T} \sum_{i=1}^{N} \ln \Big(I(s_i^j(t), s_i(t)) \cdot \frac{e^{\lambda \cdot A_i^j(t-1)}}{\sum_{k=1}^{m} e^{\lambda \cdot A_i^k(t-1)}} \Big) \tag{4}$$

where $I(s_i^j(t), s_i(t))$ is an indicator function such that $I(s_i^j(t), s_i(t)) = 1$ if $s_i(t) = s_i^j$, and 0 otherwise. The parameters of interest are $\{A(0), \lambda, \phi\}$.

Estimating a comparable model for our intergenerational treatments is different because rather than having one subject update his initial attractions over a 20 period horizon, we have subjects arriving sequentially, reading the instructions, receiving advice from their immediate predecessors, and then choosing. Hence, in the intergenerational model subjects make their choice of strategy based on their initial attractions to strategies and the advice they receive.

To formalize this let us say in the intergenerational game there are two processes: the decision making process and the advice giving process. First consider the decision making process. Assume subject i, after reading the instructions, is initially attracted to strategy s_i^k with an non-negative measure $A_i^k(0)$. If his predecessor suggests he choose strategy s_i^j, his attraction to play s_i^k will be updated as follows:

$$A_i^k = \begin{cases} A_i^k(0) + \omega & \text{if } a_i(t-1) = s_i^k \\ A_i^k(0) & \text{otherwise} \end{cases} \tag{5}$$

In other words, since subjects in our intergenerational experiments have no experience, their initial attraction to a strategy is incremented only if that strategy is the one suggested to them by their predecessor. [10]

The probability of subject i to choose strategy j at generation t is therefore

$$P_i(s_i(t) = P_i(s_i^j|A(0), \lambda_s, \omega) = \frac{e^{\lambda_s \cdot A_i^j}}{\sum_{k=1}^{m} e^{\lambda_s \cdot A_i^k}} \tag{6}$$

After he plays strategy s_i^k and receives a payoff π_i, he then gives advice to his successor. The advice he offers will be governed by a logit advice function whose arguments are the

[10]Note that the advice received is offered after the predecessor observes the outcome of his interaction with the mechanism and our subjects knows that the advice giver also received advice from his predecessor. Hence, the informational content of the advice is certainly non-zero.

attractions of the various strategies available to the subject after his experience in the game. Let V_i^k be the updated attraction of subject i for strategy k which is defined after he observes his payoff during his participation in the mechanism. V_i^k is determined as follows:

$$V_i^k = \begin{cases} A_i^k(0) + \omega + \beta(\pi_i - \min_j(\pi_i^j)) & \text{if } a_i(t-1) = s_i^k \text{ and } s_i = s_i^k \\ A_i^k(0) + \omega & \text{if } a_i(t-1) = s_i^k \text{ and } s_i \neq s_i^k \\ A_i^k(0) & \text{otherwise} \end{cases} \tag{7}$$

This attraction reinforcement rules is simple. If a subjects was told to use strategy k and followed that advice, he updates his previous attraction by $\omega + \beta(\pi_i - \min_j(\pi_i^j))$. The ω reflects the fact that his predecessor felt that strategy k was worth using while $(\pi_i - \min_j(\pi_i^j))$ reflects his personal experience with strategy k. If he was told to use strategy k but did not follow that advice, his attraction to that strategy is updated only by ω, since he failed to follow the advice of his predecessor and hence has no personal experience with strategy k. (Note, that unlike an EWA model of Camerer and Ho (1999), we do not reinforce strategy k by the counter factual payoff player i would have had if he had chosen strategy k since in this setting it is impossible for our subject to figure out what that payoff would have been. Still strategy k is given an extra weight of ω, since it was recommended.) Finally, if strategy k was neither recommended nor used, it is not reinforced at all.

Then the probability of giving advice s_i^k is determined by

$$P_i(a_i(t) = s_i^j | A(0), \lambda_a, \beta, \omega) = \frac{e^{\lambda_a \cdot V_i^j}}{\sum_{k=1}^m e^{\lambda_a \cdot V_i^k}} \tag{8}$$

Notice we assume the initial attractions to each strategy are the same in both the decision making process and the advice giving process and the advice from predecessors has the same influence, namely ω. Therefore the only difference between A_i^j and V_i^j is whether subject i used strategy s_i^j and his corresponding payoff. When determining the possibilities of which strategies to use (or to recommend), however, we allow different sensitivity with respect to attractions, that is, λ_s and λ_a may be different.

To estimate $A(0), \lambda_s, \lambda_a, \beta$ and ω, we simply pool all subjects together and form the joint likelihood as follows:

$$L(A(0), \lambda_s, \lambda_a, \beta, \omega) = \prod_i^N P_i(s_i(t) = s_i^j | A(0), \lambda_s, \omega) P_i(a_i(t) = s_i^j | A(0), \lambda_a, \beta, \omega) \tag{9}$$

The log likelihood is

$$LL(A(0),\lambda_s,\lambda_a,\beta,\omega)=\sum_{i=1}^{N}\ln\left(I(s_i^j,s_i)\cdot\frac{e^{\lambda_s\cdot A_i^j}}{\sum_{k=1}^{m}e^{\lambda_s\cdot A_i^k}}\right)+\sum_{i=1}^{N}\ln\left(I(s_i^j,a_i)\cdot\frac{e^{\lambda_a\cdot V_i^j}}{\sum_{k=1}^{m}e^{\lambda_a\cdot V_i^k}}\right) \tag{10}$$

where $I(s_i^j,s_i)$ and $I(s_i^j,a_i)$ are indicator functions such that $I(s_i^j,s_i)=1$ if $s_i=s_i^j$, and 0 otherwise, and $I(s_i^j,a_i)=1$ if $a_i=s_i^j$, and 0 otherwise.

One important feature of our estimation procedure, is that, as part of our identification strategy, we use our estimated initial attraction from the repeated Boston and Gale-Shapley treatments as exogenous to the intergenerational estimation. This is done because the intergenerational estimation is under identified unless we provide some additional information and assuming that the initial attractions are identical across repeated and intergenerational treatments is innocuous since these attractions are what subjects hold after reading the instructions for the experiment but before having any experience in the game. Hence, if our subject pools are randomly drawn, we should not expect these initial attractions to differ.

Table 3: Structural Estimation Results

	Boston	Gale-Shapley
Repeated		
$A_1(0)$	50.8492	82.1598
$A_2(0)$	0.8199	0.0693
$A_3(0)$	45.3064	69.4872
$A_4(0)$	24.4223	36.3373
$A_5(0)$	0.0572	0.0722
ϕ	0.7966	0.8936
λ	0.0781	0.0520
Observation	40	35
Log Likelihood	-501.4626	-351.4036
Intergenerational		
λ_s	0.0596	0.0415
λ_a	0.0523	0.0208
ω	20.8930	43.4409
β	2.0532	7.9401
Observation	100	100
Log Likelihood	-159.4882	-129.1849

The results are presented in Table 3. The initial attractions $A_j(0)_{j=1,\ldots,5}$ are denoted for strategies $1=\{1,2,3\},2=\{1,3,2\},3=\{2,1,3\},4=\{2,3,1\},5=\{3,1,2\}$. ($A_6(0)=\{3,2,1\}$ is normalized to 0), where the numbers in the brackets are the subjects first, second and third choice so strategy $1=\{1,2,3\}$ is a truth-telling strategy since the subject submits his first choice first, his second choice second, and his third choice last) and strategy 3={2,1,3} is a strategy where the subject places his second choice first, then his first choice and finally his third choice.

Several things are of note in Table 3. First, remember that a subject's initial attraction is his attraction to a strategy after reading the instructions but before playing the game. It is basically his intuitive response to what he thinks would be the best thing to do. In a repeated experiment this initial attraction will be updated as the subject gets experience. In the intergenerational experiment it gets updated as a result of receiving one piece of advice. What is interesting, is the fact that in both the repeated and the intergenerational treatments, the choice probabilities associated with these initial attractions, as seen in Table 3, are not particularly different across the Boston and Gale-Shapley mechanism. It implies that on first inspection, after reading the instructions, subjects are not more prone to tell the truth in the Gale-Shapley than in the Boston mechanism.

Table 4: Impact of Advice

	Boston		Gale-Shapley	
	Before Advice	After Advice	Before Advice	After Advice
1-2-3	0.4823	0.7639	0.5438	0.8787
1-3-2	0.0245	0.0801	0.0180	0.1001
2-1-3	0.3467	0.6482	0.3213	0.7420
2-3-1	0.0999	0.2781	0.0811	0.3490
3-1-2	0.0234	0.0768	0.0180	0.1001
3-2-1	0.0233	0.0765	0.0179	0.0998

However, while the initial choice probabilities do not appear to differ across mechanisms and treatments, our estimated ω parameter indicates that advice is a powerful influence on choice.[11] As can be seen in "after-advice" columns of Table 4, the probability that a subject chooses any one of his six strategies is greatly affected by whether he was advised to do so. For example, look at the truthful strategy 1-2-3. While after reading the instructions our model predicts that subjects choose this strategy with a probability

[11]We calculate the initial Probability using only the estimated values of λ_s and A_0, that is,

$$P(s_i^j) = \frac{\exp(\lambda_s A_0^j)}{\sum_i^J \exp(\lambda_s A_0^j)}$$

Then we calculated the probability of using strategy s_j if it is suggested by the previous generation, where A is updated as the following

$$A^j = A_0^j + \omega \cdot I(s_i, s_i^j)$$

where $I(s_i, s_i^j)$ is the indicator function whether s_i^j is advised. The probability of using each strategy is then calculated by

$$P(s_i^j) = \frac{\exp(\lambda_s A^j)}{\sum_i^J \exp(\lambda_s A^j)}.$$

of 48.23% in the Boston intergenerational experiment and 54.38% in the Gale-Shapley mechanism, these probabilities rise to 76.39% and 87.87% respectively after being advised to do so. A similar rise occurs when subjects are advised to use their strategic strategy 2-1-3. Finally, it is curious to note that advice even increases the probability that a subject uses an irrational strategy i.e., ones like 3-2-1 and 3-1-2, that are easily dominated. For example, while before advice a subject would be inclined to use strategy 3-1-2 with only a 1.79% probability in the Gale-Shapley intergenerational treatment, this probability rises to 9.98% if the subject is advised to do so. Advice is powerful.

Finally, there does not seem to be any important difference in the precision with which subjects choose their strategies as indicated by the estimates λ_s and λ estimates across our repeated and intergenerational treatments.

5.2 Simulation

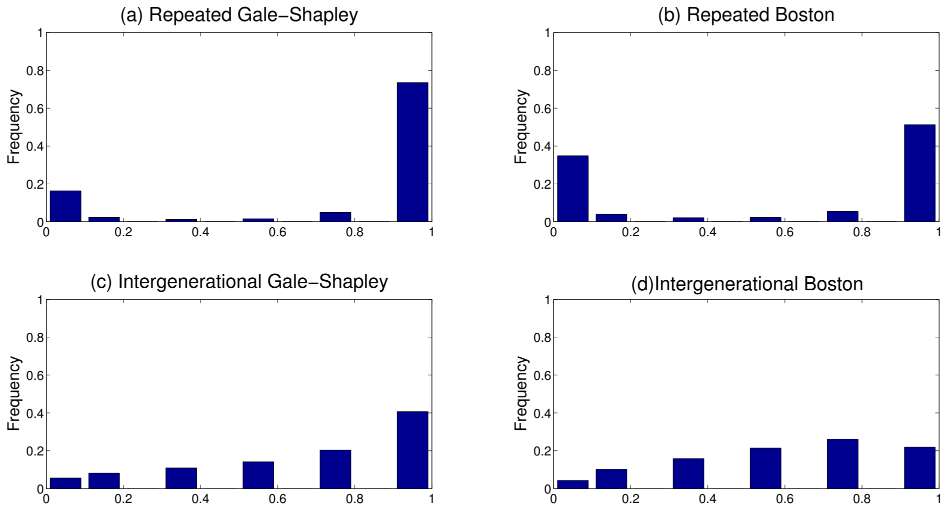
Our final exercise is to use our structural estimates to simulate behavior in the repeated and intergenerational treatments and see if we can replicate the stylized behavior exhibited in the lab. More specifically, our experiments have demonstrated that behavior is more volatile in intergenerational as compared to the repeated treatments, that truth telling in the last 10 (periods) generations is highest in the Gale-Shapley repeated treatment and significantly lower in the Intergenerational Gale-Shapley treatment, and finally that the truth telling behavior is similar across our repeated and intergenerational Boston mechanism treatments during the last 5 generations (rounds).

Truth-Telling The logic of our reinforcement learning models suggests that if our subjects were to converge on playing any given strategy, such as truth telling, then it is more likely that such convergence would occur in our repeated rather than in our intergenerational treatments. In our discussion below we use our simulation results to help us investigate this conjecture.

Figure 4 presents the frequencies, over our 10,000 simulation runs, with which subjects in our simulated five-person matching games chose truth telling during the last 5 (rounds) generations in each of our four treatments. More precisely, it presents the fraction of times the simulation ended with all five subjects reporting truthfully, 4 out of 5 reporting truthfully, down to 0 out of five doing so.

What is interesting in this figure is that the frequency with which our simulated subjects end up all reporting truthfully (i.e., converging to the truth) is dramatically higher in the repeated treatments than in the intergenerational ones. For instance, about 75% of the simulated trials ended up with all five subjects reporting truthfully in the repeated Gale-Shapley mechanism and almost 50% in the repeated Boston mechanism. These fre-

Figure 4: Simulated Truth-telling in Last 5 Rounds (Generations)

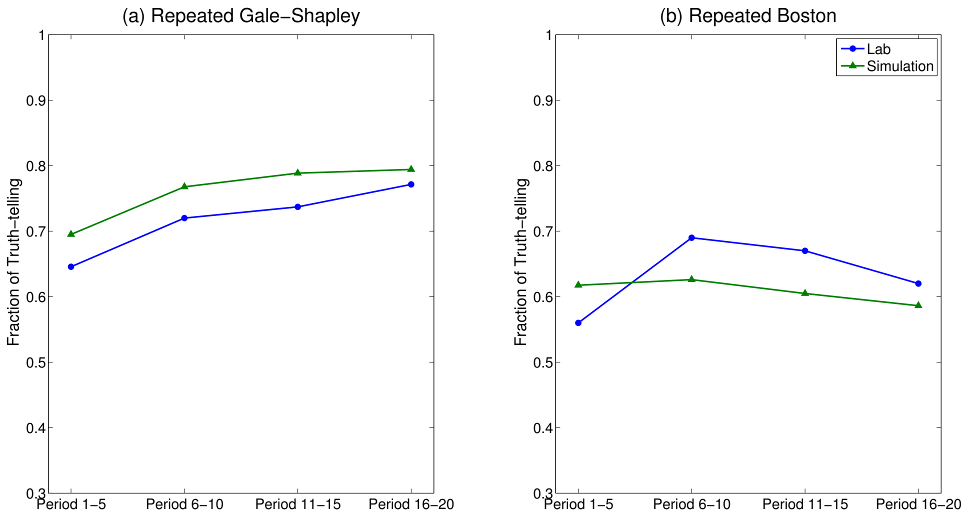


quencies are nearly twice what they are in the simulated intergenerational treatments. Further, note the bi-modal nature of the repeated treatment data with practically all subjects either all reporting the truth or close to none doing so. In the intergenerational treatments, where we expect more volatility, behavior is more spread out with substantial weight given to intermediate frequencies, between 0.4 and 0.6, suggesting greater volatility. This indicates that the dominance of truth-telling in the Gale-Shapley mechanism is relatively easily discovered if subjects are given enough experience, as they are in the repeated treatments, but not as easily in our intergenerational treatments or in the real world where parents play the matching game only a very few times in their lives. It also suggests that while the typical simulation run in the repeated treatments is likely to determine extreme outcomes (predominantly truth telling but some where no truth telling occurs) in the intergenerational treatments it is likely that we will see intermediate levels of truth telling perhaps like the 44% we observed in our intergenerational Gale-Shapley treatment.

Figure 5 is presented to both check how well calibrated our simulations are and to see if they pick up the same types of behavior as exhibited in our experiment. As suggested above, we expect our simulations to be better calibrated for the repeated treatments than for the intergenerational ones because the repeated treatments, due to the multiple number of groups performing them, are less subject to the idiosyncratic influence of the random tie-breaking lottery and other stochastic behavior of subjects like advice following and giving. Still, we expect the intergenerational simulations to pick up at least the qualitative features of the of our experimental data.

Figures 5 (a) and (b) present the actual and simulated fractions of subjects who re-

Figure 5: Simulated vs. Lab Truth-Telling Fractions in Repeated Treatments



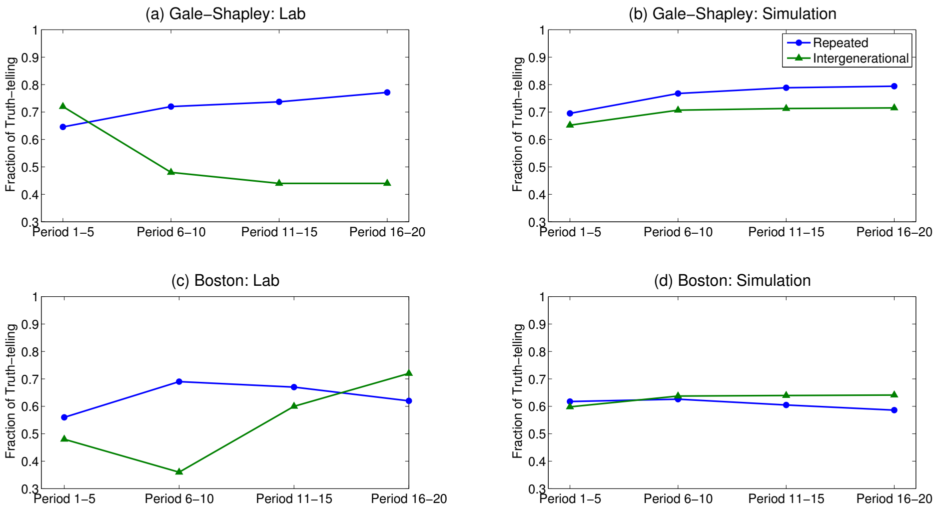
ported truthfully over the 20 rounds of the repeated Gale-Shapley and Boston treatments. As we can see, the simulations track the actual data closely and are practically identical over the last five rounds. Hence, we consider our simulations to be well calibrated for the repeated treatments.

For reasons suggested before, we do not expect our simulations to be as well calibrated when we look at the intergenerational treatments, but we do expect them to tell the same story which is that we expect that there will be more truth-telling in the repeated Gale-Shapley treatment than in the intergenerational treatment but no significant difference between the simulated repeated and intergenerational Boston treatments.

Figure 6 tells this story.

In Figure 6 (a), we see the actual time paths of the fraction of subjects reporting truthfully over the 20 rounds (generations) of the Gale-Shapley repeated and intergenerational treatments. Figure 6 (b) presents the same information as provided by our simulation. As you remember, in our experiment (Figure 1), the truth telling behavior of our subjects differed dramatically when we compared the repeated and intergenerational treatments. Toward the end of the experiment there was a significant difference between the two treatments. Figure 6 (b) demonstrates that in terms of the mean levels of truth-telling, this difference is less dramatic in our simulations. Despite these differences, however, it is still true that the fraction of subjects reporting truthfully in the simulation is significantly higher in the repeated treatment than in the intergenerational one, just as we observed in the experiment. As we will see below, the same comparison for the Boston mechanism does not lead to significant differences between the actual and simulated outcomes Hence, our simulations do replicate the stylized facts of our experiments.

Figure 6: Observed and Simulated Truth-Telling Fractions in All Treatments



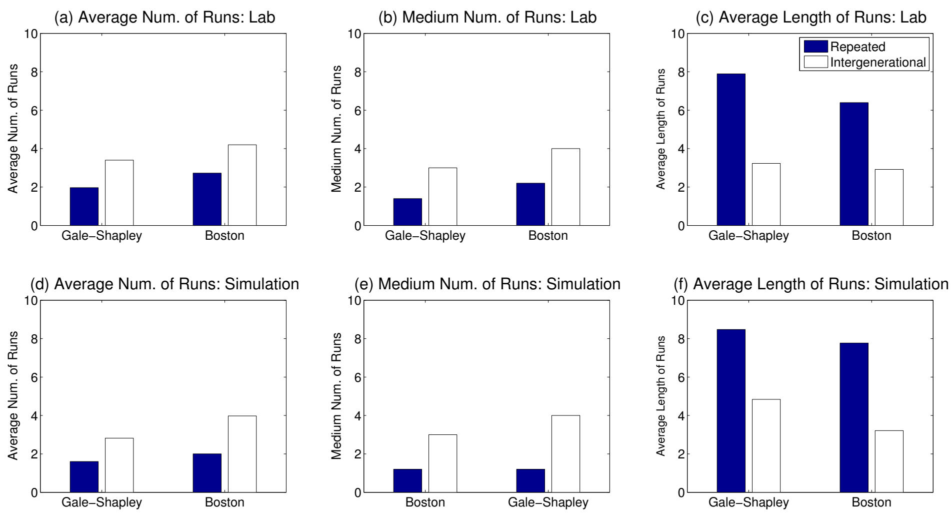
Our results are stronger than these figures suggest for the Gale-Shapley mechanism, however, since what we have presented is only a comparison of means. As we stated before, our experiment, despite involving 100 subjects, generates one and only one time series each for the Boston and the Gale-Shapley mechanisms. In the time series observed, the fraction of subjects reporting truthfully converged toward 0.44 (while our simulation converged toward 0.715). From Figure 4 (a), depicting the distribution of simulated outcomes for the Gale-Shapley mechanisms, however, we see that over the 10,000 simulation runs an outcome converging to 0.44 is not an outlier. In fact, over 25.13% of the simulation runs ended with truth telling fractions between 0.40 and 0.60 which indicates that while the mean of our one observed time series was significantly different from the mean of the simulated outcomes, observing such an outcome was rather common in the simulation. Therefore if we were to run say 10 such intergenerational experiments each generating one time series (and using 1000 subjects) we would expect to see a healthy fraction of them looking like what we saw in our experiment. If our one observed time series was an outlier with respect to the simulation, then we would have less faith in it.

Figures 6 (c) and 6 (d) make the same comparison for the Boston mechanism treatments as Figures 6 (a) and 6 (b) do for the Gale-Shapley treatments. As we can see, for the Boston mechanism, except for rounds (generations) 10 - 16, the simulation does indicate that there is no significant difference between the fraction of subjects reporting truthfully in the repeated as compared to the intergenerational Boston treatments. In addition, it also indicates that during the last 5 rounds there is more truth-telling in the Boston intergenerational than in the Boston repeated treatment, as was true in the experimental data.

In summary, our simulations did conform both qualitatively and quantitatively to our data. For the repeated treatments the fit was quite close while for the intergenerational treatments the simulations conformed qualitatively to the facts that truth-telling is significantly higher in the Gale-Shapley repeated as opposed to the Gale-Shapley intergenerational treatment and not significantly different for the Boston Mechanisms. In addition, the outcome observed in our Gale-Shapley intergenerational treatment was an outcome that had a substantial probability of being realized in our simulation.

Volatility As you recall, one of the main differences between our repeated and intergenerational treatments is that we expect to observe more volatility in our Intergenerational treatments than in our repeated ones. This was seen in Figure 3 where we presented the runs behavior across our different treatments. Figure 6 presents our volatility measures, both observed and simulated, for our four treatments

Figure 7: Observed and Simulated Volatility in Last 10 Rounds (Generations)



As can be seen, there is a great similarity between our simulated and observed results. In addition, both tell the same story which is that behavior tends to be more volatile in our intergenerational as opposed to our repeated treatments. For example, while our simulation indicates that, on average, we should expect to see runs of length 7.76 rounds during the last 10 rounds of the Repeated Boston treatment, the observed run length was 6.39 both of which were substantially larger than the observed (simulated) average run length in the Intergenerational Boston mechanism of 2.91 (3.21) generations. Similar results are observed when the Gale-Shapley mechanism is used since there, over the last 10 simulated rounds of the repeated Gale-Shapley treatment, we see an observed average run length of 8.47 while the simulated average was 7.79. The same statistics for the Gale-Shapley intergenerational treatment was 4.83 and 6.39 respectively. If there is any difference between the observed and simulated volatility results, it is that the simulated results suggest an even greater difference in volatility between repeated and intergenerational treatments.

6 Advice Giving and Receiving

In an intergenerational treatment subjects are somewhat informationally starved since the only thing they can rely on in making their decision is their interpretation of the mechanism, as manifested in their initial attractions, and the advice they receive from their immediate predecessor. In addition, as has been seen elsewhere (see Schotter and Sopher (2003, 2006, 2007) and Chaudhuri et al. (2009), and Ding and Schotter (2014)) subjects appear to be very willing to follow the advice they receive. This fact was evident in our data, since, as we saw in Table 4, the fact that subjects in our intergenerational treatments received advice had a dramatic impact of their behavior. Given that advice plays such an important role in the behavior of our subjects, it might make sense to dig a little more deeply into what factors determine both the advice giving and advice following behavior of our subjects.

6.1 Advice Giving

Our first result is very simple and is that most subjects tell their successors to do what they themselves did. In fact, 74.00% of our subjects in the intergenerational Boston mechanism and 83.00% subjects in the intergenerational Gale-Shapley mechanism suggest the same strategies they used. A breakdown of this advice-giving behavior by type is presented in Table 5.

Table 5: Fraction of Subjects Whose Advice = Action

	IB	IGS	p-value
All	0.7400	0.8300	0.1226
Type 1	0.7500	0.9000	0.2231
Type 2	0.7000	0.9000	0.1211
Type 3	0.8500	0.8000	0.6867
Type 4	0.8500	0.9500	0.3054
Type 5	0.5500	0.6000	0.7566

Table 5 demonstrates two points. One is the obvious fact that people tend to pass on advice which is equal to the action they themselves took. While this tendency might lead to social inertia or herding, i.e., people all doing the same thing and advising their

Table 6: When A Subject Suggests A Different Strategy Than What He Did

Variables	Coeff. (Std. Err)
Type 1	−0.2574
	(0.6004)
Type 2	−0.5779
	(0.5914)
Type 3	0.1985
	(0.6119)
Type 4	−1.0338
	(0.6833)
Third-best	1.6000***
	(0.5264)
Truthful	−0.6928*
	(0.3847)
Mechanism	−1.0435***
	(0.3712)
Constant	−0.1519
	(0.5092)

$*$ = significant at 10%, $**$ = significant at 5%, $***$ =significant at 1%

successors to do so as well, there is a high enough likelihood that this advice is not followed to provide the volatility we observed before. Second, except for Type 3 subjects, subjects using the Gale-Shapley mechanism are more likely to pass on advice equal to the action they took, although the difference between these treatments are not significant.

This tendency to advise what you did raises the question as to when subjects violate this rule and suggest a strategy different from the one they themselves used. To investigate this question we ran a regression where the dependent variable is an indicator variable with 1 indicating a subject suggests a strategy different from the one he chose and 0 indicating the opposite, and the independent variables include indicators for whether a subject told the truth in his matching game, whether the subject was matched with his third-best object, a set of type dummy variables and a mechanism dummy variable (0 indicating the Boston mechanism and 1 indicating the Gale-Shapley mechanism). The default situation is a Type 5 subject who used the Boston Mechanism, did not tell the truth when submitting his preference rankings, and was matched to his first or second-best object. Our results are presented in Table 7.

Several aspects of this regression are of note. First, it is interesting that no type variable is significant meaning that whether a subject suggests a strategy different from the one he used is not a function of his type. Second, it is not a surprise that a subject who ended up being matched to his third-best object would be more likely to suggest a change in strategy to his successor. However, there seems to be a built in inertia with respect to the use of the truth-telling strategy in that subjects who use it are less likely

Table 7: When A Subject Follows Advice

Variables	Coeff. (Std. Err)
Type 1	−0.1302
	(0.5380)
Type 2	0.1767
	(0.5195)
Type 3	−0.1971
	(0.5263)
Type 4	0.4800
	(0.5600)
Truthful Advice	0.9199**
	(0.3696)
Mechanism	0.4606
	(0.3445)
Constant	0.3337
	(0.4039)

$*$ = significant at 10%, $**$= significant at 5%, $***$ =significant at 1%

to tell their successors to deviate from it. Moreover there seems to be less suggested strategy changes when the Gale-Shapley mechanism is used.

6.2 Advice Following

In the advice-giving advice-following game it take two to tango. Advice offered but not followed can lead to deviations from a herd and disrupt social behavior. However such deviations may be beneficial if others are herding on inefficient or unprofitable outcomes. To investigate advice following, we run a regression to examine what factors persuade subjects to follow advice. The dependent variable is an indicator variable denoting whether a subject follows advice from his predecessor or not. The independent variables include an indicator of whether his predecessor suggested truth-telling, type variable dummies and an indicator for which mechanism was used. The default situation is a Type-5 subject who used the Boston mechanism and his predecessor was not matched to his first-best object and suggested not telling the truth.

It appears that suggesting that a subject report truthfully has a strong influence on a subject's willingness to follow advice. Note, however, that this influence is independent of which mechanism is being used since the mechanism coefficient is not significant.

7 A Quick Literature Review

The literature of school choice design was initiated by Abdulkadiroğlu and Sönmez (2003). In their pioneering paper, Abdulkadiroğlu and Sönmez formulate a "Boston mechanism" which was used in the Boston Public School System until the 2004-2005 school year. Because the Boston mechanism provides incentives for students and their parents to strategize,they propose two strategy-proof mechanisms: the Gale-Shapley deferred acceptance mechanism the outcome of which is student-optimal stable, and the Top Trading Cycles (TTC) which produces efficient allocations. Their results led a number of cities (Boston, New York City, San Francisco and New Orleans) to switch their assignment mechanisms at the urging of economist advisors (Abdulkadiroğlu, Pathak, and Roth, 005a; Abdulkadiroğlu, Pathak, Roth, and Sönmez, 005b; Abdulkadiroğlu, Featherstone, Pathak, Niederle, and Roth, 2012).

The theoretical properties of assignment mechanisms are further extended to allow more realistic assumptions to be examined. For example, there is a large branch of literature that discusses the impact of the school lottery on mechanism performance (Erdic and Ergin, 2008; Abdulkadiroğlu, Pathak, and Roth, 2009; Pathak and Sethuraman, 2011; Kesten and Ünver, 2013; Ehlers and Masso, 2007; Abdulkadiroğlu, Che, and Yasuda, 2011) and incomplete information, (Erdic and Ergin, 2008; Abdulkadiroğlu, Che, and Yasuda, 2011; Featherstone and Niederle, 2011; Abdulkadiroğlu, Che, and Yasuda, 2011). Haeringer and Klijn (2009)investigate how the equilibrium in the Gale-Shapley and the TTC mechanisms are affected by the restriction on the number of preference ranking that can be possibly reported, while Abdulkadiroğlu, Che, and Yasuda (2012) and Miralles (2008) examine the environment in which students have cardinal preference instead of ordinal ones. Overall the results about mechanism performance are mixed. Especially on the comparison between the Boston and the Gale-Shapley mechanisms, there is no clear evidence one dominates another from the perspective of efficiency.

Empirically, though there are a few papers examining school choice assignment mechanisms in the field (Abdulkadiroğlu, Pathak, and Roth, 2009; He, 2012), most of the empirical studies are done in a controlled lab environment. Chen and Sönmez (2006) is the first to compare the performances of the Boston, Gale-Shapley, and Top trading cycle mechanisms. Pais and Pintér (2008) investigate the impact of information structures on mechanism performance, while Calsamiglia, Haeringer, and Klijn (2010) examine mechanisms that allow students to only submit constrained preference lists. Featherstone and Niederle (2011) study the environment of incomplete information. Klijn, Pais, and Vorsatz (2013)investigate how individual behavior is influenced by preference intensities and risk aversion in the setting of school choice. The most recent experiment is Chen and Kesten (2013), which introduce the mechanism used in Chinese college admission and compare its performance with the Boston and the Gale-Shapley mechanisms.

As we stated above, none of the above studies, either the theoretical or the experimental ones, consider the roles of communication, advice and network structure in school choice problem. Aside from Ding and Schotter (2014), the only other paper to do so is Guillen and Hing (2013). The contribution of our experiment is to provide a close examination how this communication may affect the behavior of subjects and then influence the performance of the mechanisms.

8 Conclusion

In this paper we have attempted to investigate the impact of intergenerational advice on the behavior of subjects engaged in two school matching algorithms; the Boston and Gale-Shapley algorithms. To make an informative comparison, we ran these mechanisms in two different environments, one where subjects repeated playing the game for twenty rounds while in the other they played only once but were replaced by a next generation of player to whom they could pass on advice.

What we have found is that the introduction of an intergenerational structure has a significant influence on the behavior of our subjects and the functioning of our mechanisms. For example, when the Gale-Shapley mechanism is used and played repeated subjects appear able to learn that truth telling is a dominant strategy and hence a vast majority of subjects converge on that strategy. This is not the case when the game is played as an intergenerational game, however, where each subject plays only once and can pass advice onto the next generation. Because learning in such environments is social rather than experiential, it seems that efficient learning is disrupted As has been noted elsewhere (see Schotter and Sopher (2003, 2006, 2007) and Chaudhuri et al. (2009)), advice across generations of players appears to be a powerful force in determining behavior. Subjects tend to follow it and to pass on their behavior to their successors. However, there is enough non conformism so as to make behavior in these intergenerational treatments more volatile than in the repeated treatment we ran and hence less likely to converge to stable behavior.

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A Appendix: Experimental Instructions

A.1 Instructions for the Intergenerational Gale-Shapley Mechanism

You are about to participate in an experiment in the economics of decision making. A research foundation has provided funds to conduct this research. If you follow the instructions carefully and make good decisions, you may earn a considerable amount of money in addition to the $5 participation fee.

The currency used in this experiment is what we call "Experimental Currency Units (ECU). All payoffs will be denominated in ECU. Your earnings in ECU will be converted into U.S. dollars at the ratio of 1:0.8. Details of how you will make decisions will be provided below.

Please abide by the following rules to ensure the experiments run in optimal conditions.

• Do not talk with other participants during the experiment.

• Turn off your cell phones.

• Read the instructions carefully. If you have any questions, feel free to ask at any point during the experiment. Please do so by raising your hand and one of us will come to your desk to answer your questions.

General Structure of the Experiment

In this experiment, you will participate in two distinct decision problems, and the monetary payoff that you receive will be the sum of your payoffs in these two problems. We will first explain the details of Decision Problem 1 and then proceed to Decision Problem 2 after the first problem is done.

Decision Problem 1

As you look around the lab you will see 19 other subjects who will be participating in the experiment (20 in total). At the beginning of the first decision problem, you will be randomly divided into four groups and each group has five subjects. Subjects in each group will be assigned into types which we call Type 1, Type 2, Type 3, Type 4 and Type 5. All groups will face the same problem but the groups will make their decisions in a sequential order. More precisely, subjects in Group 1 will make their decisions first. After the subjects in Group 1 finish their decision problem, each of them will be replaced by a subject of her own type in Group 2 (her successor) who will engage in an identical decision problem. Similarly, after the participation of Group 2 subjects is over, they will be replaced by Group 3, and Group 3 will be replaced by Group 4. Group 4 subjects will be replaced by Group 1 subjects in next experimental session, so the experiment will extend beyond the session being run here. Your payoff for Decision problem 1 is determined by both your own payoff in the decision problem you participate in and the payoff of your successor in the next group. More precisely, you will receive a payoff equal to your payoff in Decision Problem 1 plus 1/2 of the payoff received by your successor in his or her decision problem. If your successor engages in a decision problem in a later session, you will collect the payment you obtain today and then will be notified when your extra payment from your successor is ready for you to pick up or we can send you your payment in the mail. Finally, when the participation of a group is over and before each subject in the group is replaced by a successor of her own type, she will be able to pass on advice to her successor about how she thinks her successor should behave. We will explain how you give such advice later in these instructions.

The Task

For each group of subjects, there are a set of 5 objects grouped into three types which we call Object A, Object B, and Object C. In particular, there are 2 units of Object A, 2 units of Object B and 1 unit of Object C. The problem is to match each of five subjects to one of the objects. We will explain how this matching works in the following section. Put simply, the matching involves each subject stating his or her ranking over objects and when this information is "inputted" into a "matching scheme," the scheme will determine the matching.

The figure below shows an example of the computer screen when you are asked to submit your ranking over objects.

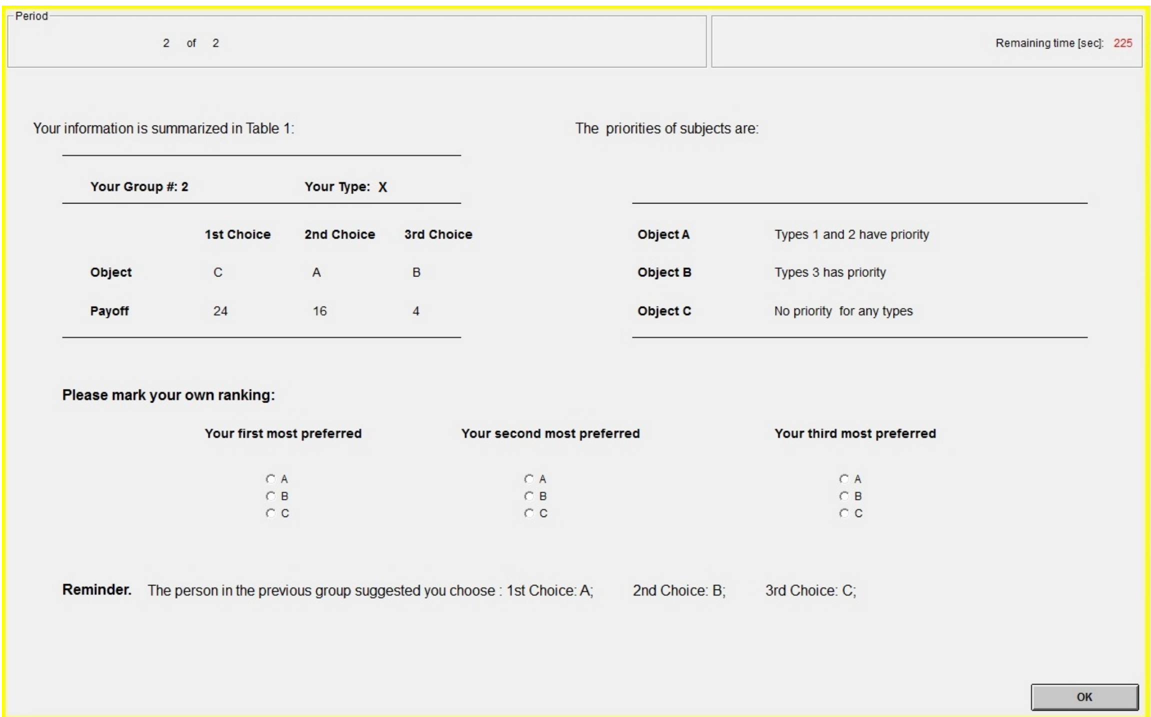


Table 1 on the upper left informs you of your group number, your type and your matching payoff of each object. In the top row of Table 1 we see this subject's group number is 1 and she is of Type X. (Here we denote the type by X but in the experiment you will be told if you are of Type 1, 2, 3, 4, or 5.) The bottom two rows show her matching value of each object. Note that this subject ranks Object C first, Object A second and Object B third. In the terms of payoffs if this subject is matched to her first choice, Object C, she will receive 24 ECU, while if she is matched to her second choice, Object A, she will receive 16 ECU, and if she is matched to Object B she will receive only 4 ECU. Other subjects will be given their information as specified by different tables but for all subjects the top ranked object will be worth 24 ECU, the second 16 ECU, and the third 4 ECU. For each group, subjects will be matched to one and only one object. You will not be told the types or the object payoffs of any subjects other than you own.

In addition to types and matching payoffs subjects will also be given priorities for certain objects, which are summarized in the upper right table. Note all subjects will receive the same priority tables. These priorities are relevant if more subjects want a kind of object than there are units available. In that case this object will be given to subjects according to their priorities. If there is more of a particular kind of object than the demand, the priorities will not matter. The priority table implies Types 1 and 2 have priority over Object A and Type 3 has priority over Object B. Then if Type 1, Type 3 and Type 5 all want Object B while there are only two units of Object B, Type 3 will be given the object first and a lottery will be held to determine whether Type 1 or Type 5 will obtain the other unit of Object B. (In later section we will describe how this lottery is run.) Finally, no types have priority over Object C, which means that if more than one subject wants object C a lottery will be held.

On the bottom of the screen there is a reminder of the advice given by the subject of your type in the previous group. A more detailed discussion of advice will be given in later sections.

The Matching Scheme

In the matching scheme each subject is required to submit a ranking over three objects. A ranking is simply a list of objects that a subject states that she prefers first, second or third, and the ranking must contain all three objects. For instance, she cannot state some object are both her first and second preferred and omit another object in her list. She will receive 24 ECU if she is assigned to her true first choice given in Table 1, 16 ECU if assigned to her true second choice, and 4 ECU if assigned to her true third choice. Note that her payoff depends on the value of the object she is matched to as defined in Table 1.

As we will see in this section describing the matching scheme, the object you will be matched with will depend on the rankings you submit, the number of subjects wanting the various objects, the priorities of the subjects wanting the same object, and the lottery used to break ties when more subjects with the same priority want the same object.

The matching scheme has nine steps and works as follows:

Step 1) All subjects enter their rankings for the objects into their computers and hit the confirm button.

Step 2) The computer will then take each subject's first ranked choice and make an application for him or her to receive that object.

Step 3) For each type of object, if the number of the applicants is less than or equal to the available number of units, all applicants will be temporarily matched to that object. Otherwise, the object will be temporarily matched to the subjects by using their priority rankings from the highest to the lowest until all units are exhausted. Low priority applicants in excess of the number of units will be left unmatched.

Step 4) If at the end of the first round all subjects are matched to objects, the temporary assignment outcome will be finalized and the scheme will end. If there are any unmatched subjects, a second round starts where all unmatched subjects are sent to their second ranked objects.

Step 5) For each type of object that receives new applicants, the computer compares the number of its remaining units with that of new applicants. If the remaining units are more than the number of new applicants, all new applicants are temporarily matched to that object. Otherwise, if the remaining units are less than the number of new applicants, these new applicants are pooled together with the subjects who were temporarily matched to that object in the previous rounds (if any.) Among these new applicants and the previously matched subjects, the objects will be temporarily matched to the subjects again by using their priority rankings from the highest to the lowest until all units are exhausted. Note, it is possible that a subject is temporarily matched in the previous rounds but left unmatched in this round, because his priority is not high enough and he gets replaced by a new applicant with a better priority number.

Step 6) If at the end of the second round all subjects are matched to objects, the temporary assignment outcome will be finalized and the scheme will end. Otherwise, if there are any unmatched subjects, a third round starts where all unmatched subjects will be sent to their next ranked objects.

Step 7) For each type of object that receives new applicants, the computer again compares the number of remaining units with that of new applicants. If the remaining units are more than the new applicants, all new applicants are temporarily matched to that object. Otherwise, if the remaining units are less than the number of new applicants, these new applicants are pooled together with the subjects that were matched with that object in the previous rounds (if any.) Among these new applicants and the previously matched subjects, the objects will be temporarily matched to the subjects by using their priority rankings from the highest to the lowest until all units are exhausted.

Step 8) The process is repeated until each subject is temporarily matched to an object. Then the temporary assignment outcome will be finalized and the scheme will end.

There is one last step required to make the scheme work. When more subjects of equal priority apply for an object than there are units available, the scheme needs a lottery to break ties. To solve this problem we need Step 9.

Step 9) At the very beginning of the matching scheme before Round 1, the computer will randomly rank subjects from first to fifth. Let us call this a types "lottery rank number." The smaller rank number a subject receives, the higher priority she is given when it comes to break ties. For example, if Type 4 and Type 5 apply for the same type of object while one is assigned a lottery rank 2 and the other lottery rank 5, the one with lottery rank 2 will be given priority over the one with rank 5 whenever ties need to be broken. Note, however, that a high lottery rank number does not supersede higher priority but only applicable among subjects who have equal priority for a type of object. That is, if Type 4 is assigned lottery rank 1 and he applies for Object B with Type 3, Type 3 will be first assigned the object no matter what the lottery rank number of Type 4 receives because Type 3 has higher priority over Object B.

An Example

We will go through a simple example to illustrate how the allocation method works. To make things simple, in this example there are four subjects, Subjects 1 to 4, and three types of objects, Object A, Object B and Object C. (Remember in our experiment there are 5 subjects and 5 objects.) Objects A and B have 1 unit each, and Object C has 2 units. Moreover, Subjects 1 and 2 have priority over Object A, and Subject 4 has priority over Object C. Subject 3 has no priority for any objects.

After all subjects submit their rankings, the computer randomly assigns each subject a "lottery rank number." For illustrative purposes, assume Subject 1 is assigned the number 3, Subject 2 is assigned the number 2, Subject 3 is assigned the number 4, and Subject 4 is assigned the number 1. Suppose subjects submitted their rankings as follows.

	Subject 1	Subject 2	Subject 3	Subject 4
1st preferred	A	A	C	A
2nd preferred	C	B	B	C
3rd preferred	B	C	A	B

The matching scheme consists of the following rounds.

1. In the first round of the scheme, every subject applies to her first choice, that is, Subject 1 applies for Object A, Subject 2 applies for Object A, Subject 3 applies for Object C, and Subject 4 applies for Object A. Given these applications, Object A is ***temporarily*** matched with Subject 2. Subject 2 is given the highest priority because she is in the high-priority class for Object A and has a higher lottery rank than the other applicant from the high-priority class, namely Subject 1. Though Subject 4 is assigned the highest lottery rank number, she is unmatched because she is in a low priority class and the lottery rank number cannot override the priority class. Object C is ***temporarily*** assigned to Subject 3 because Subject 3 is the only applicant. In the end of the first round Subject 1 and 4 are left unmatched.

2. In the second round, the unmatched Subjects 1 and 4 apply for their second choices, Object C. As there is only 1 unit of Object C left while there are two new applicants, Subject 1, 3 and 4 are pooled together and Object C are assigned by using their priority rankings. Subject 4 is first ***temporarily*** matched as she is in the high priority class for Object C. Then Subject 1 is ***temporarily*** matched because both Subject 4 and she are in the low-priority class for Object C but she is assigned a higher lottery rank. In the end of the second round, Subject 3 is left unmatched.

3. In the third round, the unmatched Subject 3 applies for his second choice, Object B. Since Object B still has one unit left, Subject 3 is matched with Object B.

4. As all subjects have been temporarily matched, the outcome is finalized and the scheme ends.

5. The final matching is therefore as follows:

Subject 1 is matched with Object C.

Subject 2 is matched with Object A.

Subject 3 is matched with Object B.

Subject 4 is matched with Object C.

Note that in this example as in the experiment every subject will be matched with an object.

Matching Payoff

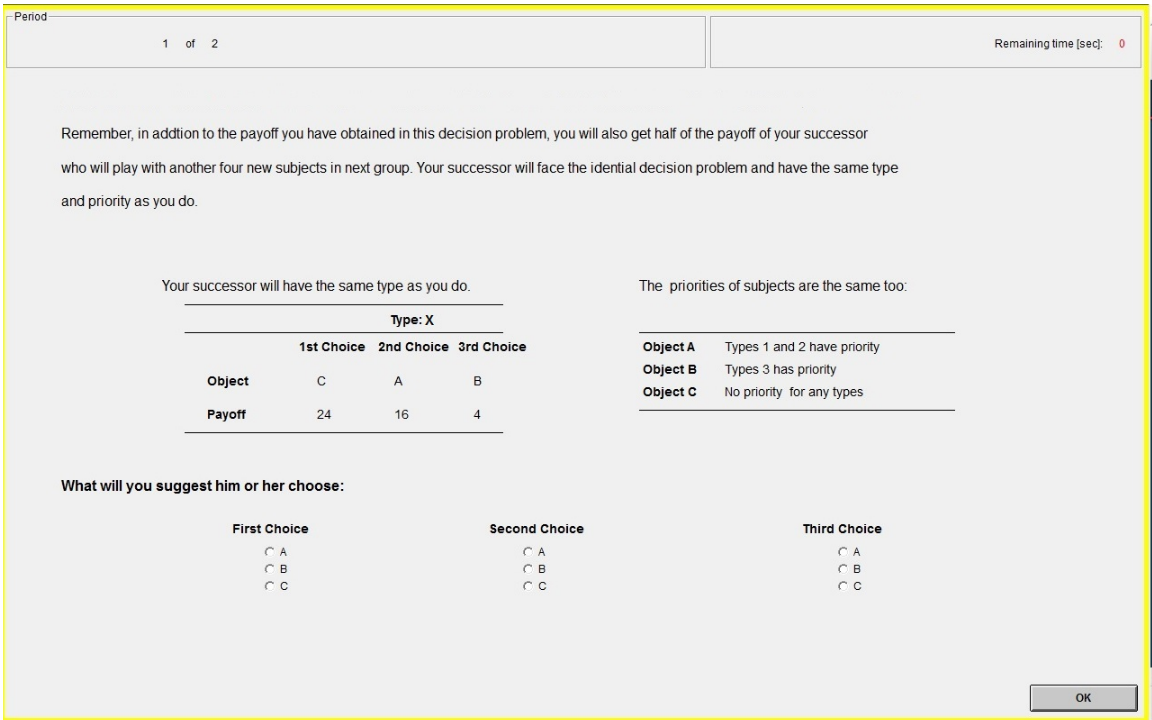
In this decision problem the payoff of any subject will simply be equal to the value of the object she is matched to, i.e., she will receive 24 ECU if she is assigned to her true first choice given in Table 1, 16 ECU if assigned to her true second choice, and 4 ECU if assigned to her true third choice.

Your final payoff and Your Successor

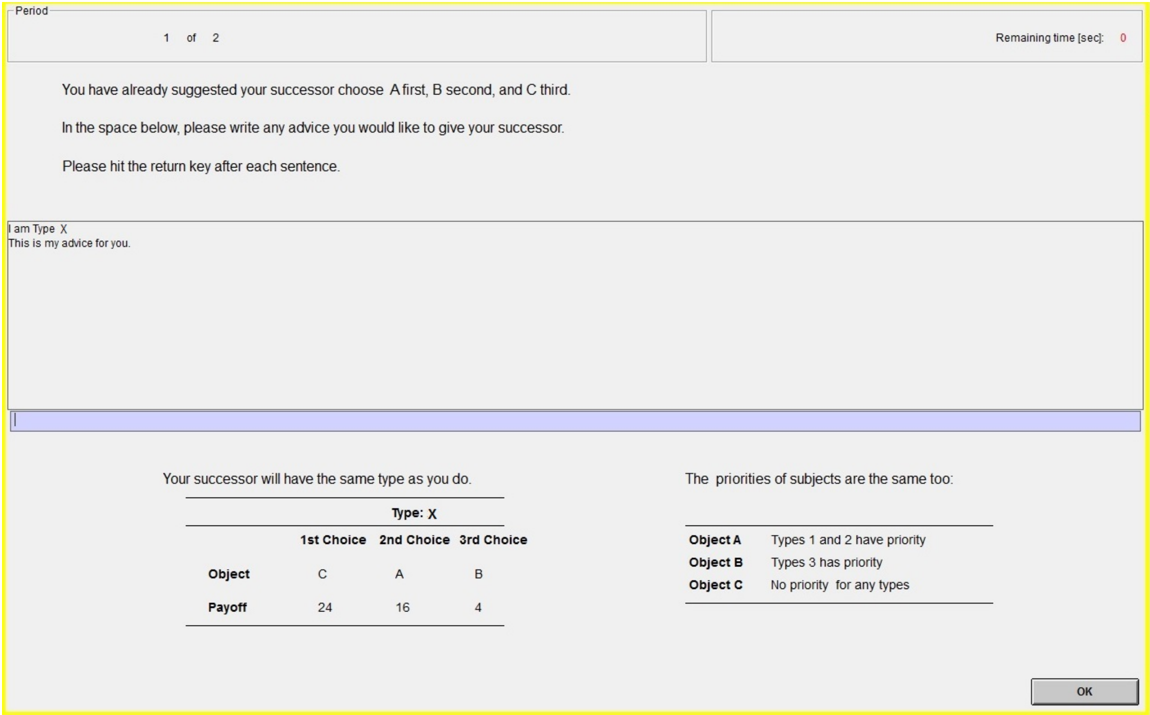
As we mention at the very beginning of the instruction, after you finish your participation in this decision problem, another subject in next group will take your role and face the identical decision problem with a new set of four other subjects. For example, if you are Type 1 in Group 1, there will be another subject assigned into Type 1 in Group 2 and he or she will have the exact payoff of each object as you do. Your final payoff will be determined by both your own payoff in the decision problem you participate in and by the payoff of your successor in the decision problem that he or she participates in. More specifically, you will earn the sum of your payoffs in the decision problem you participate in plus an amount equal to one half of the payoff of your successor in his or her decision problem.

<u>Advice to Your Successor</u>

Since your payoff depends on how your successor behaves, we will allow you to give advice to your successor in private after you review your match and corresponding payoff. The advice consists of two parts. You are first asked to recommend a ranking of objects which your successor should rank first, second and third. In the example of computer screen on next page, the subject is of Type X and she is asked to submit her recommendation for her successor who is also assigned into Type X.



After submitting your suggestion and clicking OK button, you will navigate to a new screen which provides a space to write comments for your successor about the choice he or she should make. As shown in the example of the computer screen on next page, you can type messages in the box where the cursor is. Hit the enter key after each sentence and the messages will then be shown in the advice box. You may write any information you believe relevant to the choices of your successor. If you wish, you may also tell your successor which choices you have made and your final allocation and payoff in the problem you have participated in.



Unless you are the first person ever to participate in Decision Problem 1, you will see the advice given by the person in the previous group as soon as you start the problem.

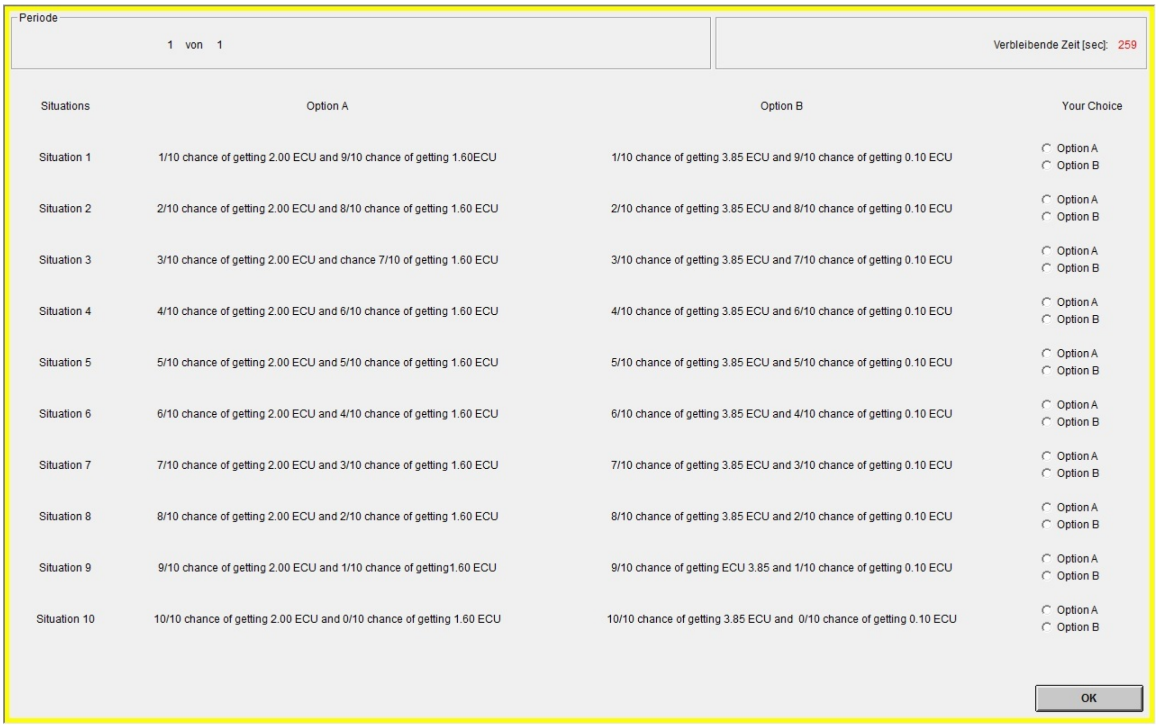
Summary

In sum, Decision Problem 1 will proceed as follows. Subjects are assigned to one of four groups and the groups will make their decisions in a sequential order. When it is time for your group to make decisions, you will first see a recommended rank of objects and advice given by the person of your own type in the previous group. You are then asked to state your preference over objects by ranking which is your most preferred, which is your second most preferred, and which is your third most preferred. After the matching scheme determines the object you are matched to and the corresponding payoff, you will leave your advice to your successor.

Decision Problem 2

This is a totally different decision problem than Problem 1. Your task is to choose between two lottery tickets that are denoted “Option A” and “Option B.” You will make ten choices but only one of them will be used to determine your earnings. Each decision has an equal chance of being selected, but you will not know in advance which decision will be used. The figure above shows the computer screen you will face.

Look at the first situation in the figure. If you choose Option A, there is a 1/10 chance that you earn 2.00 ECU while 9/10 chance that you earn 1.60 ECU. If you choose Option B, you have a 1/10 chance to earn 3.85 ECU and 9/10 chance to earn 0.10 ECU. Other



Periode

1 von 1

Verbleibende Zeit [sec]: 259

Situations	Option A	Option B	Your Choice
Situation 1	1/10 chance of getting 2.00 ECU and 9/10 chance of getting 1.60ECU	1/10 chance of getting 3.85 ECU and 9/10 chance of getting 0.10 ECU	Option A / Option B
Situation 2	2/10 chance of getting 2.00 ECU and 8/10 chance of getting 1.60 ECU	2/10 chance of getting 3.85 ECU and 8/10 chance of getting 0.10 ECU	Option A / Option B
Situation 3	3/10 chance of getting 2.00 ECU and chance 7/10 of getting 1.60 ECU	3/10 chance of getting 3.85 ECU and 7/10 chance of getting 0.10 ECU	Option A / Option B
Situation 4	4/10 chance of getting 2.00 ECU and 6/10 chance of getting 1.60 ECU	4/10 chance of getting 3.85 ECU and 6/10 chance of getting 0.10 ECU	Option A / Option B
Situation 5	5/10 chance of getting 2.00 ECU and 5/10 chance of getting 1.60 ECU	5/10 chance of getting 3.85 ECU and 5/10 chance of getting 0.10 ECU	Option A / Option B
Situation 6	6/10 chance of getting 2.00 ECU and 4/10 chance of getting 1.60 ECU	6/10 chance of getting 3.85 ECU and 4/10 chance of getting 0.10 ECU	Option A / Option B
Situation 7	7/10 chance of getting 2.00 ECU and 3/10 chance of getting 1.60 ECU	7/10 chance of getting 3.85 ECU and 3/10 chance of getting 0.10 ECU	Option A / Option B
Situation 8	8/10 chance of getting 2.00 ECU and 2/10 chance of getting 1.60 ECU	8/10 chance of getting 3.85 ECU and 2/10 chance of getting 0.10 ECU	Option A / Option B
Situation 9	9/10 chance of getting 2.00 ECU and 1/10 chance of getting1.60 ECU	9/10 chance of getting ECU 3.85 and 1/10 chance of getting 0.10 ECU	Option A / Option B
Situation 10	10/10 chance of getting 2.00 ECU and 0/10 chance of getting 1.60 ECU	10/10 chance of getting 3.85 ECU and 0/10 chance of getting 0.10 ECU	Option A / Option B

OK

situations are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, there is no uncertainty for each option and so your choice is simply to choose between 2.00 ECU and 3.85 ECU. To summarize, you will make ten choices: for each decision row you will have to choose between Option A and Option B. You may choose A for some decision rows and B for other rows.

Once you have made all ten decisions, click on OK button. Then the computer will first randomly select one situation and then run a lottery to determine your payment. For example, if Situation 9 is randomly selected and you chose option A in that case, then you get 2.00 ECU with probability 9/10 and 1.60 ECU with probability 1/10.

A.2 Instructions for the Intergenerational Boston Mechanism

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The Matching Scheme

In the matching scheme each subject is required to submit a ranking over three objects. A ranking is simply a list of objects that a subject states that she prefers first, second or third, and the ranking must contains all three objects. For instance, she cannot state some object are both her first and second preferred and omit another object in her list. She will receive 24 ECU if she is assigned to her true first choice given in Table 1, 16 ECU if assigned to her true second choice, and 4 ECU if assigned to her true third choice.

Note that her payoff depends on the value of the object she is matched with as defined in Table 1.

As we will see in this section describing the matching scheme, the objects you will be matched with will depend on the rankings you submit, the number of subjects wanting the various objects, the priorities of the subjects wanting the same object, and the lottery used to break ties when more people with the same priority want the same object.

The matching scheme has seven steps and works as follows:

Step 1) All subjects enter their rankings for the objects into their computer and hit the confirm button.

Step 2) The computer will then take each subject's stated first choice.

Step 3) For each type of object, if the number of the applicants is less than the available number of units, all applicants are matched with the object for which they applied. Otherwise, this type of object will be allocated to the applicants by using their priority rankings from the highest to the lowest until all units are exhausted. Low-priority applicants in excess of the number of units will be left unmatched.

Step 4) If at the end of the first round all subjects are matched with objects, the matching process is over. If there are unmatched subjects, a second round starts where all unmatched subjects are sent to their second ranked objects.

Step 5) In the second round, for each type of object, if there are still units available and the number remaining is greater than the number of new applicants, all new applicants are matched with the object for which they applied. Otherwise, this type of object will be allocated to the applicants by using their priority rankings from the highest to the lowest until all remaining units are exhausted. If this type of object has already run out in the first round, all new applicants are left unmatched.

Step 6) The scheme ends if each subject is assigned to an object by the end of the second round. Otherwise, the remaining unassigned subjects are assigned to their last choices.

There is one last step required to make the scheme work. When more subjects of equal priority apply for an object than there are units available, the scheme needs a lottery to break ties. To solve this problem we need step 7.

Step 7) At the very beginning of the matching scheme before round 1, the computer will randomly rank the subjects from first to twentieth. Let us call this a type's "lottery rank number." The smaller rank number a subject receives, the higher priority she is given when it comes to break ties. For example, if a type 4 subject and a type 5 subject apply to the same type of object while one is assigned a lottery rank 2 and the other lottery rank 5, the one with lottery rank 2 will be given priority over the one with rank 5 whenever ties need to be broken. Note, however, that a high lottery rank number does not supersede higher priority classes but only gives priority to subjects in the same priority class. If a type 4 subject is assigned lottery rank 1 and he applies for Object B with another type 3 subject, the type 3 will be first assigned the object no matter what the "lottery rank number" of type 4 subject receives because type 3 is in the high priority class. The lottery rank number is only applicable among subjects who have equal priority for a type of object.

An Example

We will go through a simple example to illustrate how the allocation method works. To make things simple, in this example assume there are four subjects, 1-4, and three type of objects, Object A, B and C (Remember in our experiment there are 20 subjects and 20 objects.) Objects A and C have 1 unit each, and Object B has 2 units. Moreover, Object A gives priority to Subjects 1 and 2, and Object C gives priority to Subject 4. Subject 3 has no priority for any objects.

After all subjects submit their rankings, the computer randomly assigns each subject a "lottery rank number." For illustrative purpose, assume Subject 1 is assigned the number 2, Subject 2 is assigned the number 1, Subject 3 is assigned the number 3, and Subject 4 is assigned the number 4. Suppose subjects submitted their rankings as follows.

	Subject 1	Subject 2	Subject 3	Subject 4
1st preferred	A	A	C	C
2nd preferred	C	B	B	A
3rd preferred	B	C	A	B

The matching scheme consists of the following rounds.

1. In the first round of the procedure, every subject applies for her first choice, that is, Subject 1 applies for Object A, Subject 2 applies for Object A, Subject 3 applies for Object C, and Subject 4 applies for Object C. Given these applications, Object A is matched with Subject 2. This is true because even though both Subjects 1 and 2 belong to the high priority class for Object A, Subject 2 receives the lottery rank 1, which is higher than that of Subject 1. Object C is matched with Subject 4, because Subject 4 is in the high priority class for Object C. Though Subject 3 receives a higher lottery rank than Subject 4, the lottery rank cannot override the priority class. In the end of the first round, Subject 1 and 3 are left unmatched.

2. In the second round, the unmatched Subjects 1 and 3 apply for their second choices: Subject 1 applies for Object C, and Subject 3 applies for Object B. Since there are no more Object C's is left, Subject 1 is unmatched. Subject 3 is matched with object B.

3. In the third round, the unmatched Subject 1 applies for his third choice, Object B. Since Object B still has one unit left, Subject 1 is matched with Object B and the

mechanism stops.

4. The final matching is therefore as follows:

Subject 1 is matched with Object B.

Subject 2 is matched with Object A.

Subject 3 is matched with Object B.

Subject 4 is matched with Object C.

Note that in this example as in the experiment every subject will be matched with an object.

A.3 Instructions for the Repeated Gale-Shapley Mechanism

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The currency used in this experiment is what we call "Experimental Currency Units" (ECU). All payoffs will be denominated in ECU. Your earnings in ECU will be converted into U.S. dollars at the ratio of 1:1. Details of how you will make decisions will be provided below.

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Decision Problem 1

As you look around the lab you will see 19 other subjects who will be participating in the experiment (20 in total). At the beginning of the first decision problem, you will be randomly assigned into types in the sense that among these 20 subjects four of you will be of Type 1, four will be of Type 2, four will be of Type 3, four will be of Type 4 and four will be of Type 5. You will participate in Decision Problem 1 for 20 periods. **Your type will remain the same in each of these 20 periods.** At each period you will be randomly divided into four groups and each group will have five subjects. In particular, every subject in a group will have a different type. i.e., there will be one subject each of Type 1, Type 2, Type 3, Type 4 and Type 5. After each period we will randomly match you with four other subjects so that you will not interact with the same subjects over the entire 20 periods of Decision Problem 1 but rather get a new set of subjects chosen randomly at each period.

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Final Payoffs

As stated before, your type (i.e., your matching payoff of each object and your priority right) will remain the same at all periods and you will face the same matching problem. At the end of the 20th period of Decision Problem 1, a lottery will be drawn to determine which period is payoff relevant. For instance, suppose the lottery determines you will be paid for Period 9, you will be paid 24 ECU if you are matched to your true first choice as specified in Table 1, 16 ECU if assigned to your true second choice, and 4 ECU if assigned to your true third choice in that period.