Preference Intensities and Risk Aversion in School Choice: An Experimental Study*

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Abstract

We experimentally investigate in the laboratory two prominent mechanisms that are employed in school choice programs to assign students to public schools. We study how individual behavior is influenced by risk aversion and the relative distribution of payoffs. Our two main results show that (a) the Gale–Shapley mechanism is more robust to changes in cardinal preferences than the Boston mechanism independently of whether individuals are allowed to submit a complete or a restricted ranking over the set of schools and (b) subjects with a higher degree of risk aversion are more likely to play "safer" strategies under the Gale–Shapley but not under the Boston mechanism.

Keywords: school choice, risk aversion, preference intensities, laboratory experiment, Gale–Shapley mechanism, Boston mechanism, efficiency, stability, constrained choice.

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1 Introduction

In recent years a steadily growing literature has looked into the design of mechanisms to assign children to public schools. School choice programs give families a say in the assignment of their children to schools. The seminal paper by Abdulkadiroğlu and Sönmez [5] applied matching theory to propose concrete solutions to design school choice mechanisms that solve problems experienced in real–life applications. Several economists were invited to meetings with the school district authorities of Boston and New York City to explore possible ways to redesign the assignment procedures. It was decided to adopt variants of the so–called deferred acceptance mechanism due to Gale and Shapley [15], also called the Gale–Shapley mechanism.[1] Since many other US school districts use variants of what was baptized the Boston mechanism, it is not unlikely that these first redesign decisions lead to similar adoptions elsewhere in the near future.

Chen and Sönmez [10] turned to controlled laboratory experiments and compared the performance of the Boston mechanism with the Gale–Shapley mechanism. Their results suggest that the Gale–Shapley mechanism outperforms the Boston mechanism in terms of efficiency. A number of experimental studies have been carried out to further study the performance of the mechanisms. For instance, in many real–life applications, agents are only allowed to submit a list containing a limited number of schools. Calsamiglia *et al.* [9] analyse the impact of imposing such a constraint and show that, as a consequence, manipulation is drastically increased and both efficiency and stability of the final allocations are affected. Another important issue concerns the level of information agents hold on the preferences of the others. Pais and Pintér [23] focus on this comparing environments where agents have complete information with environments where agents, while aware of their own preferences, have no information at all about the preeferences of their peers. A different approach is taken in Featherstone and Niederle [13], where agents do not know the preferences of the others, but instead are aware of their underlying distribution. In both papers, it turns out that strategic behavior is driven by the environment and the mechanism under analysis, with corresponding effects on the final allocation, and also on the ranking between Gale–Shapley and Boston. Finally, Echenique *et al.* [12] is an attempt to disentangle the effects of several characteristics

[1] Abdulkadiroğlu, Pathak, and Roth [2], [3] and Abdulkadiroğlu, Pathak, Roth, and Sönmez [4] report in detail on key issues in the redesign.

of the matching market under the Gale–Shapley mechanism alone, highlighting the importance of the number of stable matchings and of the cardinal representation of agents' preferences.

The need of reassessing the school choice mechanisms is reinforced by the recent theoretical findings in Abdulkadiroğlu, Che, and Yasuda [1]. They showed that in typical school choice environments the Boston mechanism Pareto dominates the Gale–Shapley mechanism in *ex ante* welfare. What drives this result is that the Boston mechanism induces participants to reveal their cardinal preferences (*i.e.*, their relative preference intensities) whereas the Gale–Shapley mechanism does not.[2] In view of this and other results Abdulkadiroğlu *et al.* [1] caution against a hasty rejection of the Boston mechanism in favor of mechanisms such as the Gale–Shapley mechanism.[3]

Motivated by these recent findings we experimentally compare the performance of different school choice mechanisms. We opt for a stylized design that has several important advantages. *First*, by letting subjects participate repeatedly in the same market with varying payoffs, we are able to investigate the impact of preference intensities on individual behavior and welfare. *Second*, a special feature of our laboratory experiment is that before subjects participate in the matching markets they go through a first phase in which they have to make lottery choices. This allows us to see whether subjects with different degrees of risk aversion behave differently in the matching market. *Third*, the complete information and the simple preference structure form an environment that can be thought through by the subjects. Hence, clear theoretical predictions about how preference intensities and risk aversion should affect behavior can be made. *Fourth*, our setup purposely does not recur to similar ordinal preferences and schools with coarse priorities in order to avoid possible problems in entangling the causes of observed behavior.[4] In other words, we are able to isolate the effect of cardinal preferences and risk aversion on behavior in school choice mechanisms. *Finally*, our experimental study also serves as a validation device for results found in previous (less stylized) studies that are potentially closer to practice but possibly not completely satisfactory in terms of identifying the motivation of individual behavior.

Our main results are as follows. For the (ordinal) preference structure used in our experiment,

[2] On the other hand, the Gale–Shapley mechanism elicits truthful revelation of ordinal preferences whereas the Boston mechanism does not.

[3] Miralles [20] drew a similar conclusion based on his analytical results and simulations.

[4] Similar ordinal preferences and coarse priorities are two common features of many school choice environments.

the distribution of submitted rankings does not depend on whether the Gale–Shapley or the Boston mechanism is used, yet constraining the number of schools subjects are allowed to rank affects individual behavior significantly (Result 1). This extends some of the recent findings in Calsamiglia *et al.* [9] for truth–telling to distributions of rankings. With respect to the effect of cardinal preferences, the simple economic intuition that subjects tend to rank a school higher (lower) if the payoff of that particular school is increased (decreased) everything else equal, can be verified. Since we also find that every significant change in behavior provoked by variations in the preference intensity under the Gale–Shapley also happens under the Boston mechanism and since there are some significant effects that occur under the Boston but not under the Gale–Shapley mechanism, we can conclude that the Gale–Shapley mechanism is more robust to changes in cardinal preferences than the Boston mechanism (Result 2). Using the distribution of submitted rankings, we then calculate the welfare properties of the different mechanisms. We find that Gale–Shapley outperforms Boston if the mechanism is unconstrained but that Boston outperforms Gale–Shapley for the constrained mechanisms (Result 3), which is mainly driven by the fact that the percentage of student optimal matchings is higher for Gale–Shapley in the unconstrained and for Boston in the constrained setting (Result 4). Then, we employ Tobit and Probit ML estimations to see whether individual behavior in the matching market is correlated with the degree of risk aversion obtained from the lottery choices. Our analysis shows that subjects with a higher degree of risk aversion are more likely to play protective strategies if the Gale–Shapley algorithm is applied but not when the Boston mechanism is used (Result 5).[5] Finally, we divide our subject pool into two subgroups —one subgroup containing all subjects who revealed a "high" degree of risk aversion in the lottery choice phase and one subgroup containing the remaining subjects with a "low" degree of risk aversion— and analyze how behavior within each of the two subgroups is affected by preference intensities. It turns out mainly that the negative impact of constraining the number of submittable schools on efficiency under the Gale–Shapley mechanism is stronger for the highly risk averse (Result 6).

The remainder of the paper is organized as follows. The experimental design is explained in Section 2. In Section 3, we derive hypotheses regarding the effect of cardinal preferences and risk aversion on strategic

[5] Loosely speaking, a subject plays a protective strategy if she protects herself from the worst eventuality to the extent possible. Consequently, a protective strategy is a maximin strategy.

behavior. A first preliminary analysis of aggregate behavior and the impact of changes in cardinal preferences is given in Section 4. In Section 5 we look into the levels of efficiency and stability obtained under the mechanisms, as well as their responsiveness to changes in cardinal preferences. Section 6 is devoted to risk aversion. In Section 7 we conclude with some possible implications for policy–makers. Sample instructions and some additional estimation results are relegated to the Appendices.

2 Experimental Design and Procedures

Our experimental study comprises four different treatments. Each treatment is divided into two phases. In the first phase, which is identical for all treatments, we elicit the subjects' degree of risk aversion using the paired lottery choice design introduced by Holt and Laury [19].[6] To be more concrete, subjects are given simultaneously ten different decision situations (see Table 1). In each of the ten situations, they have to choose one of the two lotteries available.

Situation	Option A	Option B	Difference
1	(1/10 of 2.00 ECU, 9/10 of 1.60 ECU)	(1/10 of 3.85 ECU, 9/10 of 0.10 ECU)	1.17 ECU
2	(2/10 of 2.00 ECU, 8/10 of 1.60 ECU)	(2/10 of 3.85 ECU, 8/10 of 0.10 ECU)	0.83 ECU
3	(3/10 of 2.00 ECU, 7/10 of 1.60 ECU)	(3/10 of 3.85 ECU, 7/10 of 0.10 ECU)	0.50 ECU
4	(4/10 of 2.00 ECU, 6/10 of 1.60 ECU)	(4/10 of 3.85 ECU, 6/10 of 0.10 ECU)	0.16 ECU
5	(5/10 of 2.00 ECU, 5/10 of 1.60 ECU)	(5/10 of 3.85 ECU, 5/10 of 0.10 ECU)	-0.18 ECU
6	(6/10 of 2.00 ECU, 4/10 of 1.60 ECU)	(6/10 of 3.85 ECU, 4/10 of 0.10 ECU)	-0.51 ECU
7	(7/10 of 2.00 ECU, 3/10 of 1.60 ECU)	(7/10 of 3.85 ECU, 3/10 of 0.10 ECU)	-0.85 ECU
8	(8/10 of 2.00 ECU, 2/10 of 1.60 ECU)	(8/10 of 3.85 ECU, 2/10 of 0.10 ECU)	-1.18 ECU
9	(9/10 of 2.00 ECU, 1/10 of 1.60 ECU)	(9/10 of 3.85 ECU, 1/10 of 0.10 ECU)	-1.52 ECU
10	(10/10 of 2.00 ECU, 0/10 of 1.60 ECU)	(10/10 of 3.85 ECU, 0/10 of 0.10 ECU)	-1.85 ECU

Table 1: The Holt and Laury [19] paired lottery choice design. For each of the ten decision situations, we also indicate the expected payoff difference between the two lotteries. Since we did not want to induce a focal point, subjects were not informed about the expected payoff difference during the experiment.

It can be seen from Table 1 that in the first decision situation, the less risky lottery (Option A) has a higher expected payoff than the more risky one (Option B). Hence, only very strong risk lovers pick Option B in this situation. As we move further down in the table, the expected payoff difference between the two lotteries decreases and eventually turns negative in situation 5. Consequently, risk

[6] This procedure, called "multiple price list," has been widely used. Recent applications include Blavatskyy [8] and Heinemann *et al.* [18].

neutral subjects prefer Option A in the first four and Option B in the last six decision situations. In the last decision situation, the subjects have to choose between a sure payoff of 2.00 ECU (Option A) and a sure payoff of 3.85 ECU (Option B). Since all rational individuals prefer the second option, all risk averse subjects will also have switched by then from Option A to Option B. Finally, observe that rational individuals switch from Option A to Option B at most once (they may always prefer Option B) but never from Option B to Option A, and that the more risk averse an individual is the further down in the table she switches from Option A to B.

After subjects have decided which lottery to choose in each of the ten decision situations, they enter the second phase of the experiment in which they face the following stylized school choice problem: There are three teachers (denoted by 1, 2, and 3) and three schools (denoted by X, Y, and Z). Each school has one open teaching position. The preferences of the teachers over schools and the priority ordering of schools over teachers, both commonly known to all participants, are presented in the following table.

	Preferences			Priorities		
	Teacher 1	Teacher 2	Teacher 3	School X	School Y	School Z
Best match (30 ECU)	X	Y	Z	2	3	1
Second best match	Y	Z	X	3	1	2
Worst match (10 ECU)	Z	X	Y	1	2	3

Table 2: Preferences of teachers over schools (left) and priority orderings of schools over teachers (right).

It can be seen from Table 2 that the preferences of the teachers form a Condorcet cycle. The priority orderings of the schools form another Condorcet cycle in such a way that every teacher is ranked last in her most preferred school, second in her second most preferred school, and first in her least preferred school. During the experiment, subjects assume the role of teachers that seek to obtain a job at one of the schools. They receive 30 ECU in case they end up in their most preferred school and 10 ECU if they obtain a job at their least preferred school. The payoff of the second most preferred school is the same for all participants but varies in the course of the second phase. Initially it is set at 20 ECU, then it becomes 13 ECU, and finally it is 27 ECU.

The task of the subjects in the second phase is to submit a ranking over schools (not necessarily the true preferences) which will be used by a central clearinghouse to assign teachers to schools. So, schools are not strategic players. We consider a total of four different treatment conditions (2×2–design) that are known to be empirically relevant in this type of market. The first treatment variable refers to the restrictions on the rankings teachers can submit. We consider the *unconstrained* and one *constrained* setting. In the unconstrained setting, teachers have to report a ranking over all three schools, while in the constrained setting, they are only allowed to report the two schools they want to rank first and second. The second treatment variable refers to how reported rankings are used by the central clearinghouse to assign teachers to schools. We apply here both Gale–Shapley's deferred acceptance algorithm (GS) and the Boston algorithm (BOS). For the particular school choice problem at hand, they are as follows:

Step 1. Each teacher sends an application to the school she ranked first.

Step 2. Each school retains the applicant with the highest priority and rejects all other teachers.

Step 3. Whenever a teacher is rejected at a school, this teacher sends an application to her next highest ranked school.

Step 4. The two algorithms differ only in the way they treat new applications.

(GS) Whenever a school receives new applications, these applications are considered together with the previously retained application (if any). Among the retained and the new applications, the teacher with the highest priority is retained, all other teachers are rejected.

(BOS) Whenever a school receives new applications, all of them are rejected in case the school already retained an application before. In case the school did not retain an application so far, it retains among all applicants the one with the highest priority and all other teachers are rejected.

Step 5. The procedure described in Steps 3 and 4 is repeated until no more applications can be rejected. Each teacher is finally assigned to the school that retains her application at the end of the process. In case none of a teacher's applications are retained at the end of the process, which can only happen in the constrained mechanisms, this teacher remains unemployed and gets 0 ECU.[7]

[7] If teachers had to rank only one school, the two constrained mechanisms would be identical; that is, for all submitted profiles of preferences, the same matching would be obtained under the Gale–Shapley and under the Boston mechanims. This is the main reason why we forced subjects to rank two schools in the constrained setting.

Combining the two treatment variables we obtain our four treatment conditions; the Gale–Shapley unconstrained mechanism (abbreviated, GS_u); the Boston unconstrained mechanism (BOS_u); the Gale–Shapley constrained mechanism (GS_c); and, the Boston constrained mechanism (BOS_c). Also, to maintain the notation as simple as possible, GS_{c27} will refer to the situation in treatment GS_c where the payoff of the second most preferred school is 27 ECU. All other situations are indicated accordingly.

The experiment was programmed within the z–Tree toolbox provided by Fischbacher [14] and carried out in the computer laboratory at the Universitat Autònoma de Barcelona between June and September 2009. We used the ORSEE registration system by Greiner [16] to invite students from a wide range of faculties. In total, 218 undergraduates participated in the experiment. We almost obtained a perfectly balanced distribution of participants across treatments even though some students did not show up.

Each session proceeded as follows. In the beginning of the experiment, each subject only received instructions for the first phase (that included some control questions) together with an official payment receipt. Subjects could study the instructions at their own pace and any doubts were privately clarified. Participants were also informed that they would play afterwards a second phase, without providing any information about its structure. Subjects also knew that their decisions in phase 1 would not affect their payoffs in the other phase (to avoid possible hedging across phases) and that they would not receive any information regarding the decisions of any other player until the end of the experiment (so that they could not condition their actions in the second phase on the behavior of other participants in the first phase). In theory, therefore, the two phases are independent from each other.

After completing the first phase, subjects were anonymously matched into groups of three (within each group, one subject became teacher 1, one subject teacher 2, and one subject teacher 3) and entered the second phase of the experiment, where they faced one of the four matching protocols. The roles within the groups remained the same throughout the second phase. Subjects were informed that three different school choice problems would be played sequentially under the same matching protocol within the same group, but they did not know how the parameters would change in the course of the second phase. It was also made clear that no information regarding the co–players' decisions, the induced matching, or the resulting payoffs would be revealed at any point in time. No feedback whatsoever was provided. This prevented subjects from conditioning their decision on former actions of other group members and avoids issues with learning. We informed subjects about the first payoff constellation (the salary at the second school is 20 ECU) in the instructions. The case in which the second school pays 13 ECU (27 ECU) was always played second (last). When playing the second school choice game, subjects had no information regarding the parameter choices in the third school choice game.

To prevent income effects, either phase 1 or 2 was payoff relevant (one participant determined the payoff relevant phase by throwing a fair coin at the end of the experiment), which was known by the subjects from the beginning. If the first phase was payoff relevant, the computer selected randomly one of the ten decision situations. Given the randomly selected decision situation, the uncertainty in the lottery chosen by the subject then resolved in order to determine the final payoff. If the second phase was payoff relevant, the computer randomly selected one of the three payoff constellations. Subjects were then paid according to the resulting matching in that particular payoff constellation. At the end of the experiment, subjects were informed about the payoff relevant situation and their final payoff. Subjects received 4 Euro (40 Eurocents) per ECU in case the first (second) phase was paid. These numbers were expected to induce similar expected payoffs. A session lasted about 75 minutes and subjects earned on average 12.21 Euro for their participation including a 3 Euro show–up fee.[8]

3 Experimental Hypotheses

In this section, we derive our experimental hypotheses regarding the effects of cardinal preferences and risk aversion. Since the school choice problem is set up symmetrically, the three teachers face exactly the same decision problem and we can simplify the description of the strategy spaces. More precisely, we will make use of the notation (2,1,3) for the ranking where a teacher ranks her second most preferred school first, her most preferred school second, and her least preferred school last. The other five strategies (1,2,3), (1,3,2), (2,3,1), (3,1,2), and (3,2,1) have similar interpretations. Also, even though subjects are restricted to apply to two schools only in the constrained setting, the strategy space has the same cardinality as in the unconstrained setting and in fact the same notation can be used. For example, the notation (1,2,3) means then that the subject ranks her first school first, her second school second, and that she does not

[8]Some exemplary instructions translated from Spanish can be found in Appendix A.

apply to her last school. Finally, note that the strategies (3,1,2) and (3,2,1) are strategically equivalent for all four mechanisms; that is, they always yield the same payoff independently of the behavior of the other group members (they yield a payoff of 10 ECU for sure). Although possibly not all subjects were aware of the strategic equivalence of (3,1,2) and (3,2,1), we nevertheless decided to pool these two strategies in our analysis through the notation (3,×,×).

With respect to the question of which strategies could be observed, probably the least restrictive assumption is that rational subjects do not play dominated strategies. Proposition 1 derives the set of undominated strategies for each of the four mechanisms we employ.

Proposition 1 *The sets of undominated strategies are as follows:*[9]

Mechanism	Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
Gale–Shapley unconstrained	×				
Gale–Shapley constrained	×	×		×	
Boston unconstrained	×		×		
Boston constrained	×	×	×	×	×

We describe the underlying intuition of Proposition 1.[10] It is well known that the Gale–Shapley mechanism is strategy–proof in the unconstrained setting (see Dubins and Freedman [11] and Roth [24]); that is, it never hurts to report preferences truthfully. One easily verifies that with our particular profile of priorities any other strategy gives a strictly lower payoff for some submittable rankings of the other two players. Therefore the only undominated strategy in GS_u is truth–telling. With respect to treatment GS_c, Haeringer and Klijn [17] showed that it never pays off to report a constrained ranking where the two listed schools are reversed with respect to the true preferences. In fact, one readily verifies that in our particular situation (*i.e.*, priority profile) the three strategies that "respect" the true binary relations are the only undominated strategies.

Regarding BOS_u, it never hurts to report school 3 —one's truly last school— last because the worst thing that can happen is ending up in that school. Since acceptance is no longer deferred, there are submittable rankings of the other two players for which it is strictly better to report the ranking (2,1,3)

[9] A given strategy is undominated under a given mechanism if and only if the corresponding entry is ×.
[10] A formal proof is available from the authors upon request.

than (1,2,3). Indeed, some simple but tedious calculations show that these two strategies are the only undominated strategies in BOS_u. Finally, in BOS_c, acceptance is not deferred, and in addition there is a constraint on the length of submittable rankings. In this environment it can actually be better to report a lower ranked school above a higher ranked one. As a consequence all strategies are undominated in this treatment. Our prediction about how variations in the cardinal preference structure affect individual behavior in this market is as follows.

Prediction 1 *Subjects no longer list school 2 or list school 2 further down in their submitted ranking if the payoff of this school decreases from 20 ECU to 13 ECU. Similarly, subjects no longer exclude school 2 from their submitted ranking or list school 2 further up in their ranking if the payoff of this school increases from 20 ECU to 27 ECU.*

The economic intuition behind this prediction is fairly simple. Whenever the payoff of a school decreases everything else equal, its relative attractiveness decreases. Consequently, subjects who originally rank school 2 above some other school(s) may decide to push it further down their ranking or not list it at all. A symmetric argument applies if the payoff of school 2 is increased. Combining Proposition 1 and Prediction 1 we obtain finally the following table that reflects our hypothesis of how the use of undominated strategies changes due to variations in cardinal preferences.

Mechanism	Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
Gale–Shapley unconstrained					
Change from 20 to 13 ECU	=				
Change from 20 to 27 ECU	=				
Gale–Shapley constrained					
Change from 20 to 13 ECU	−	+		−	
Change from 20 to 27 ECU	+	−		+	
Boston unconstrained					
Change from 20 to 13 ECU	+		−		
Change from 20 to 27 ECU	−		+		
Boston constrained					
Change from 20 to 13 ECU	?	+	−	−	+
Change from 20 to 27 ECU	?	−	+	+	−

Table 3: Hypothesis about how variations in cardinal preferences affect the play of *undominated* strategies.

We explain the hypothesis for each mechanism for the case when the payoff of the second school is reduced from 20 ECU to 13 ECU (the hypotheses regarding an increase to 27 ECU are similar). We first consider the two Gale–Shapley mechanisms. There should not be any effect in treatment GS_u, simply because truth–telling is the only undominated strategy for this mechanism. In treatment GS_c, only the strategies (1,2,3), (1,3,2), and (2,3,1) are undominated. Subjects who initially play (1,3,2) will also do so after the reduction of the payoff. Also, subjects who initially tell the truth may change to play (1,3,2) instead. Finally, subjects who initially play (2,3,1) could be tempted to play (3,2,1) or (3,1,2), as suggested by our prediction. However, these strategies are dominated by (2,3,1) and (1,3,2), respectively. Hence, if a subject who initially played (2,3,1) changes his strategy, then we expect him to play (1,3,2). So, when the second school pays 13 ECU the strategies (1,2,3) and (2,3,1) will be played less often and (1,3,2) will be played more often compared to the situation where the second schools pays 20 ECU.

We now consider the two Boston mechanisms. According to Proposition 1, only the strategies (1,2,3) and (2,1,3) are undominated in BOS_u. Clearly, every individual who tells the truth under the original payoffs will still prefer to tell the truth when the payoff of school 2 is reduced. On the other hand, subjects who initially played the strategy (2,1,3) may switch to telling the truth. Consequently, our hypothesis states that the change in the payoffs makes subjects report more often the ranking (1,2,3) and less often the ranking (2,1,3). Finally, we consider BOS_c. Here, every strategy is undominated. Similarly to GS_c, subjects who initially play (1,3,2) will also do so after the reduction of the payoff, and subjects who initially tell the truth may change to play (1,3,2) instead. Individuals who submitted the ranking (3,×,×) opt for the school that guarantees access and a payoff reduction of school 2 should not make them start taking risks. However, subjects who initially chose (2,3,1) may now submit the riskless strategy (3,×,×) so that this strategy could be played more often after the reduction of the payoff. Finally, subjects who initially played (2,1,3) could possibly change to (1,2,3) or (1,3,2). All in all, strategies (1,3,2) and (3,×,×) will be played more often, and strategies (2,1,3) and (2,3,1) will be played less often. Since there are two opposite effects regarding strategy (1,2,3), we do not make a prediction regarding the change in truth–telling.

The first phase of the experiment gives us the possibility to explain behavior in the market we study in terms of the subjects' characteristics, namely in terms of their attitude towards risk. Since the subjects receive full information about individual preferences, priorities, and payoffs and, also, the four mechanisms do not include any randomness, the only source of uncertainty is strategic: Subjects have to form subjective beliefs about the other group members' strategies. So, for instance they have to ponder the economic benefits from working at their top school against the probability that another subject with a higher priority for that school applies and graps the slot. To develop a prediction regarding the behavior of *highly risk averse* subjects, we make use of the concept of *protective strategies* provided in Barberà and Dutta [6].[11] Loosely speaking, when an agent has no information about the others' submitted preferences, she behaves in a protective way if she plays a strategy so as to protect herself from the worst eventuality to the extent possible. In our setup this means, for any distribution over the others' strategy profiles: First, choosing a strategy that guarantees access to a school; second, among these, if possible, one that maximizes the probability of obtaining school 1 or 2; and finally, within this set of strategies and whenever possible, picking one that maximizes the probability of being matched to school 1.

Prediction 2 *Highly risk averse subjects tend to employ protective strategies in the matching market.*

We can easily check Prediction 2 since protective strategies in our matching market can readily be calculated. In fact, since under GS_u telling the truth never hurts and, for some strategy profiles of the others, leads to better matching partners, truth–telling is the unique protective strategy under this mechanism.[12] In contrast, under BOS_u, a subject gains by manipulating the true preferences and submitting $(2, 1, 3)$ against some complementary preference profiles, while, against others, she ends up better off by submitting the true preferences. This, together with the fact that by ranking school 3 at the bottom of the list, the subject reduces the set of complementary profiles for which she is assigned to her lowest ranked option, explains why $(1, 2, 3)$ and $(2, 1, 3)$ are (the only) protective strategies under BOS_u.

In what constrained mechanisms are concerned, in our matching market, protective behavior ensures, in the first place, that a subject is not left unassigned for any profile of complementary strategies. This implies using strategy $(3, \times, \times)$ under BOS_c —the unique protective strategy under this mechanism— and, given that acceptance is deferred in GS_c, ranking school 3 first or second in the list under this

[11]Two settings in which protective strategies have been studied are two-sided matching markets (Barberà and Dutta [7]) and, more recently, paired kidney exchange (Nicolò and Rodríguez-Alvárez [22]).

[12]Barberà and Dutta [6] show that under GS_u truth–telling is the unique protective strategy for all participants on both sides of a *two-sided* matching market.

mechanism. Moreover, given that ranking school 3 second increases the chances of being assigned to a school better than 3, both $(1,3,2)$ and $(2,3,1)$ are protective. We summarize this in Proposition 2.[13]

Proposition 2 *The sets of protective strategies are as follows:*[14]

Mechanism	Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
Gale–Shapley unconstrained	×				
Gale–Shapley constrained		×		×	
Boston unconstrained	×		×		
Boston constrained					×

4 Aggregate Behavior and Cardinal Preferences

In this section, we first present aggregate data and analyze whether and how the empirical distribution of submitted rankings changes according to the applied matching mechanism. Afterwards, we will provide evidence regarding the first hypothesis formulated in Section 3.

Mechanism	Submitted Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
Gale–Shapley unconstrained					
20 ECU	**0.5000**	0.0000	0.4074	0.0370	0.0556
13 ECU	**0.6481**	0.0370	0.1852	0.0185	0.1110
27 ECU	**0.4444**	0.0000	0.4259	0.0741	0.0555
Gale–Shapley constrained					
20 ECU	0.2407	0.1852	0.1481	**0.3148**	0.1110
13 ECU	0.1667	**0.3148**	0.0926	0.2778	0.1482
27 ECU	0.2037	0.1296	0.2593	**0.3148**	0.0926
Boston unconstrained					
20 ECU	**0.4000**	0.0182	**0.4000**	0.1636	0.0182
13 ECU	**0.6182**	0.0364	0.1455	0.0727	0.1273
27 ECU	0.3091	0.0000	**0.5455**	0.0909	0.0545
Boston constrained					
20 ECU	**0.2727**	0.2000	0.1455	0.2545	0.1272
13 ECU	0.1818	**0.3636**	0.1273	0.1636	0.1636
27 ECU	0.1455	0.0545	0.2727	**0.4364**	0.0909

Table 4: Probability distribution of the submitted rankings. The most salient rankings for a given mechanism and cardinal preferences are indicated in boldface.

[13] A formal proof is available from the authors upon request.

[14] A given strategy is protective under a given mechanism if and only if the corresponding entry is ×.

It can be seen from Table 4 that the most salient ranking is always an undominated strategy. It also follows from inspecting the column (1,2,3) that for each payoff constellation and among all four mechanisms, the level of truth–telling is highest in GS_u. This is not a surprise because it is the only mechanism for which truth–telling is the unique undominated strategy (Proposition 1). However, since the level of truth–telling falls well short of 100 % in this treatment as well, several subjects did not recognize that it is in their best interest to reveal preferences honestly.[15]

Next, we use χ^2 tests for homogeneity to investigate whether the distribution of the submitted rankings depends on the actual mechanism.[16] We find that for both the unconstrained and the constrained setting, the empirical distribution under the Boston mechanism is not significantly different from the distribution under the Gale–Shapley mechanism. More precisely, the p–values when comparing GS_u with BOS_u are 0.0700 if school 2 pays 20 ECU, 0.3600 if school 2 pays 13 ECU, and 0.3450 if school 2 pays 27 ECU. The corresponding p–values of the tests that compare the treatments GS_c and BOS_c are 0.4850, 0.2550, and 0.1550. On the other hand, imposing a constraint on the number of schools a teacher can submit seems to have a considerable effect on behavior. Truth–telling is considerably lower in the constrained setting (see Footnote 15) while the strategies (1,3,2) and (2,3,1), which are both dominated in the unconstrained setting, see now a substantial amount of play. Indeed, it turns out that the one–sided p–values of the χ^2 tests between GS_u and GS_c (and between BOS_u and BOS_c) are equal to 0.0001 independently of the payoff of the second most preferred school. We summarize our findings so far as follows.

Result 1 (Empirical distributions of rankings: constraint and GS vs. BOS.) *For all cardinal preference constellations, the distribution of submitted rankings in treatment GS_u (BOS_u) is significantly different from the one in treatment GS_c (BOS_c). On the other hand, for all cardinal preference constellations, the distributions of submitted rankings in treatments GS_u and BOS_u (GS_c and BOS_c) are not significantly different from each other.*

[15] In Chen and Sönmez [10], in their "random" and "designed" treatments of GS_u, 56% and 72% of the subjects, respectively, submitted their true preferences. The numbers are 58 % and 57 % in Calsamiglia *et al.* [9]. Overall our numbers seem to be slightly lower but a real comparison is not possible due to the very different environments. Using Z tests for two proportions one can easily verify that for all three cardinal preferences constellations, the level of truth–telling in GS_u (BOS_u) is significantly higher than in GS_c (BOS_c), which is consistent with the findings in Calsamiglia *et al.* [9]. On the other hand, there is no significant difference between GS_u and BOS_u nor between GS_c and BOS_c.

[16] The null hypothesis of these tests states that the probability with which any of the five strategies is played does not depend on the mechanisms that are compared. Consequently, the null hypothesis is rejected if the probability is significantly different for at least one of the five strategies. Also note that throughout the analysis reported p–values are always one–sided.

We now turn our attention to the question of how the cardinal preferences influence individual behavior in the matching market we study. The relevant data is provided in Table 5, which shows the percentage changes in the probability distribution over the submitted rankings when the payoff of the second school decreases from 20 to 13 ECU (top part of the table) and when it increases from 20 to 27 ECU (bottom part of the table). For the sake of completeness, we also include the p–values of the χ^2 tests for homogeneity that analyze whether the respective distributions of submitted rankings differ.

Mechanism	Rankings					p–value
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)	
20 ECU − 13 ECU						
Gale–Shapley unconstrained	-0.1481	-0.0370	0.2222	0.0185	-0.0555	*0.0300*
Gale–Shapley constrained	0.0741	-0.1296	0.0556	0.0370	-0.0370	*0.2300*
Boston unconstrained	-0.2182	-0.0182	0.2545	0.0909	-0.1091	*0.0002*
Boston constrained	0.0909	-0.1636	0.0182	0.0909	-0.0364	*0.1450*
20 ECU − 27 ECU						
Gale–Shapley unconstrained	0.0556	0.0000	-0.0185	-0.0370	0.0000	*0.4650*
Gale–Shapley constrained	0.0370	0.0556	-0.1111	0.0000	0.0185	*0.3300*
Boston unconstrained	0.0909	0.0182	-0.1455	0.0727	-0.0364	*0.1400*
Boston constrained	0.1273	0.1455	-0.1273	-0.1818	0.0364	*0.0100*

Table 5: Changes in the probability distribution of the submitted rankings. A positive (negative) number indicates that the corresponding ranking is used more (less) often when the payoff is 20 ECU. We also present the one–sided p–value of the χ^2 test for homogeneity that analyzes whether the empirical distribution depends on the cardinal preference constellation.

We see that a reduction of the payoff of school 2 from 20 to 13 ECU changes the distribution of submitted rankings in the unconstrained but not in the constrained setting, while raising its payoff from 20 to 27 ECU only affects the distributions in treatment BOS_c. In order to analyze this general finding in more detail, we run additional Wilcoxon signed ranked tests as they allow us to see which particular ranking is submitted less or more often due to the change in the cardinal preferences.

First, we discuss significant changes in behavior related to the reduction of the payoff of school 2. With respect to the unconstrained mechanisms, we find that the reduction makes subjects use the strategy (2,1,3) significantly less often ($p = 0.0163$ in GS_u and $p = 0.0053$ in BOS_u), while, at the same time, subjects also tell significantly more often the truth ($p = 0.0007$ in GS_u and $p = 0.0003$ in BOS_u). These results have only been predicted in BOS_u because telling the truth is the unique undominated strategy in GS_u. We also find that in treatment BOS_u, the ranking (2,3,1) is submitted significantly less ($p = 0.0294$)

and the rankings (3,×,×) significantly more ($p = 0.0072$) often after the change of payoffs. Although according to Proposition 1 neither of the two strategies should have been used at all, it seems "natural" that some of the subjects who did not realize that these strategies are dominated switch from the ranking (2,3,1) to (3,×,×) as the payoff of school 2 decreases. With respect to the constrained mechanisms, we find the same significant effect for both GS_c and BOS_c: The strategy (1,3,2) is applied more often after the change ($p = 0.0261$ in GS_c and $p = 0.0145$ in BOS_c), which is in line with our hypothesis. So, all significant changes that take place under Gale–Shapley also occur under Boston independently of whether the constrained or unconstrained setting is applied and there is no significant change in the submitted rankings that is in the opposite direction to that of our hypothesis. Still, some significant changes we observe in the data are not covered by our hypothesis as they are related to undominated strategies, but neither of them contradicts Prediction 1.

Second, we discuss significant changes in the probability distribution over the submitted rankings that are due to an increase of the payoff of school 2 from 20 to 27 ECU. It can be seen from the bottom part of Table 5 that individual behavior is mainly affected in the Boston treatments. For example, in BOS_u, the ranking (2,1,3) is submitted more often after increasing the payoff of school 2 ($p = 0.0105$). Similarly, in treatment BOS_c, subjects reveal less often their preference truthfully ($p = 0.0354$), they submit the ranking (1,3,2) less often ($p = 0.0105$), they use the strategy (2,1,3) more frequently ($p = 0.0354$), and they play the strategy (2,3,1) more often after the payoff has been changed ($p = 0.0092$). Observe that all significant changes regarding Boston are according to our hypothesis. Finally, since the only significant effect in the Gale–Shapley treatments is that subjects submit the ranking (2,3,1) more often after increasing the payoff of school 2 ($p = 0.0289$), it is again the case that all changes in behavior caused by the variation in cardinal preferences under Gale–Shapley take also place under Boston. Consequently, we can summarize our findings as follows.

Result 2 (Empirical distributions of rankings: cardinal preferences.) *The Gale–Shapley mechanism is more robust to changes in cardinal preferences than the Boston mechanism, independently of whether choice is unconstrained or constrained.*

5 Performance: Efficiency and Stability

Two prominent indicators of the performance of matching mechanisms are efficiency and stability. While efficiency for teachers[17] is the primary welfare goal, stability of the matchings reached should be met for the mechanism to be "successful."[18] In our setup, a matching is blocked if there is a teacher that prefers to be assigned to some school with a slot that is either available or occupied by a lower priority teacher. A matching is stable if it is not blocked. An important advantage of our simple environment is that we can actually compare the different mechanisms on these two important dimensions directly, *i.e.*, without recurring to (virtual) recombinations and estimations.

5.1 Efficiency

To determine the levels of efficiency, we first calculate the likelihood of every profile of submitted preference rankings from the empirical distributions over all possible strategies presented in Table 4. For each such profile, we then determine the induced matching and the resulting average payoff per teacher. The overall efficiency is finally computed as the expected average payoff per teacher. To be able to compare the efficiency for different cardinal preferences under the same mechanism, we normalized the payoff of school 2 to 20 ECU independently of its actual value. The results are depicted in Table 6.

Mechanism	Payoff second most preferred school		
	20 ECU	13 ECU	27 ECU
Gale–Shapley unconstrained	21.1024	22.6871	20.6662
Gale–Shapley constrained	17.4156	16.7522	17.7509
Boston unconstrained	20.6802	22.1641	20.1635
Boston constrained	18.0584	18.2426	17.8447

Table 6: Efficiency (expected average payoff per teacher in ECU).

Our first observation is that for both the Gale–Shapley and the Boston mechanisms, the expected payoff per teacher is always higher in the unconstrained setting than in the constrained setting. This is not surprising as all teachers who stay unemployed in the constrained mechanism would automatically get assigned to their third ranked school in the corresponding unconstrained mechanism. More interest-

[17]For efficiency we only consider the welfare of the teachers as the school slots are mere objects.
[18]Stability is important to avoid potential law suits or the appearance of matches that circumvent the mechanism.

ingly, payoffs are not necessarily lower under the Boston than under the Gale–Shapley mechanism. In fact, whereas Gale–Shapley delivers slightly higher levels of efficiency than Boston in the unconstrained case, it turns out that efficiency is always higher in BOS_c than in GS_c. Two elements may contribute to the observed differences across mechanisms. First, the mechanisms produce different outcomes for some strategy profiles. This can be accounted for by looking at the efficiency levels when the uniform distribution over profiles of strategies is considered. In our preference setup, as far as the uniform distribution is concerned, BOS_u exhibits an *a priori* advantage over GS_u, whereas BOS_c and GS_c deliver approximately the same levels of efficiency.[19] It thus follows that the observed differences in efficiency must rely on a second element, namely, that individuals behave differently when confronted with different mechanisms. An inspection of Table 4 reveals that the proportion of truth–telling under GS_u is higher than under BOS_u, which is reflected in the efficiency ranking of the two mechanisms. On the other hand, whereas GS_c and BOS_c lead to roughly the same strategic choices when school 2 is worth 20 ECU, differences are more pronounced for the other payoff constellations, resulting in a visible efficiency advantage of BOS_c over GS_c when school 2 is valued 13 ECU.

Result 3 (Efficiency.) *Imposing a constraint reduces efficiency. Moreover, GS_u outperforms BOS_u, but BOS_c outperforms GS_c. Finally, increasing the payoff of school 2 leads to a reduction of efficiency, except for treatment GS_c.*

5.2 Stability

Table 7 contains the total proportion of stable matchings reached given the empirical distribution of the submitted preference rankings in each treatment (in boldface), split into the three stable matchings labeled teacher optimal, compromise, and school optimal. Under each of these symmetric matchings, every teacher is assigned to its most valued, second most valued, and least valued school, respectively.

We can see that, for every mechanism, the number of times the compromise stable matching is reached increases sharply as the payoff of school 2 rises. Under GS_c, this is obtained mainly at the expense of the school optimal stable matching —valued at 10 ECU per teacher— thus resulting in an improvement

[19]For the uniform distribution, the average payoff per teacher is 15.42 ECU under GS_u and 16.94 ECU under BOS_u, while reaching 14.58 ECU and 14.91 ECU under their constrained counterparts.

Mechanism	Payoff second most preferred school		
	20 ECU	13 ECU	27 ECU
Gale–Shapley unconstrained	**0.8571**	**0.7196**	**0.8629**
Teacher optimal	0.1250	0.3216	0.0878
Compromise	0.7173	0.3458	0.7545
School optimal	0.0148	0.0522	0.0205
Gale–Shapley constrained	**0.5505**	**0.4944**	**0.5934**
Teacher optimal	0.0773	0.1116	0.0370
Compromise	0.3344	0.1503	0.4621
School optimal	0.1388	0.2324	0.0943
Boston unconstrained	**0.6558**	**0.4491**	**0.6760**
Teacher optimal	0.0731	0.2805	0.0295
Compromise	0.5775	0.1039	0.6333
School optimal	0.0051	0.0647	0.0132
Boston constrained	**0.3441**	**0.3089**	**0.6034**
Teacher optimal	0.1056	0.1622	0.0080
Compromise	0.1949	0.0708	0.5760
School optimal	0.0435	0.0759	0.0194

Table 7: Stability (proportions of stable matchings, split into the teacher optimal, the compromise, and the school optimal stable matchings).

in efficiency, whereas under both GS_u and BOS_u, efficiency decreases as the teacher optimal stable matching —worth 30 ECU per teacher— is reached far less often. Simultaneously, the proportion of stable matchings reached as a whole increases. Under BOS_c, the prominent increase in the proportion of the compromise stable matching rests mainly on the number of unstable matchings, boosting both stability and efficiency as the payoff of school 2 increases.

When comparing different treatments for the same payoff constellation, the numbers suggest that imposing a constraint significantly reduces the probability of obtaining a stable matching. The same result was obtained in Calsamiglia *et al.* [9] for the Gale–Shapley mechanism. On the other hand, Gale–Shapley is in general more successful than Boston in producing stable matchings. This is in line with theory in the unconstrained case —since Gale-Shapley produces stable matchings when subjects are truthful, whereas Boston does not— and again with Calsamiglia *et al.* [9]. Finally, note that when the magnitude of the changes in the percentage of stable matchings obtained is taken into account, it appears to be the case that, very much in accordance with Result 2, the Gale–Shapley mechanism is less sensitive than Boston to changes in the payoff of school 2. In fact, when comparing the percentage of stable matchings reached when school 2 is worth 13 and 27 ECU, differences in stability reach 0.1432 and 0.0992 under GS_u and GS_c, respectively, against 0.2269 and 0.2944 under BOS_u and BOS_c.

Result 4 (Stability.) *Imposing a constraint reduces stability. Moreover, GS is more stable and "stability–robust" to changes in payoffs than BOS. Finally, increasing the payoff of school 2 increases stability, mainly due to the compromise stable matching.*

6 Risk Aversion

In this section, we analyze whether subjects with different degrees of risk aversion —proxied by the switching point in the paired lottery choice phase— behave differently in the matching market and whether this depends on the actual mechanism employed. To investigate this question, we study how the distribution of submitted rankings changes as the subjects with the lowest switching point in the paired lottery choice phase are eliminated step–by–step from our subject pool. This procedure can be readily described as follows: We start by considering the distribution of submitted rankings for the whole subject pool. Then, in the first step of the process, we analyze how this distribution changes as we eliminate from our subject pool all those subjects who, in the first phase of the experiment, switch from Option A to Option B in the first decision situation.[20] In the second step of the process, we eliminate from our subject pool all those subjects who switch from Option A to Option B in the second decision situation. This process continues until we are only left with the subjects who switch earliest in the ninth decision situation. The advantage of this procedure is that it does not only allow us to determine if individual behavior depends on risk aversion, but it also enables us to establish the degree of risk aversion from which on behavior differs.

The relevant data is presented in Figure 1. It consists of four panels, one for each treatment. In every panel, the horizontal axis indicates switching points in the paired lottery choice phase. On the vertical axis, we plot the percentage with which the subjects who have a switching point that is at least as high as the number indicated on the horizontal axis play any of the possible five strategies. Consequently, as we move from the left to the right in a given graph, the subjects with the lowest risk aversion among all those still considered are discarded.[21] This procedure has the potential drawback that the distribution of

[20] We consider this to be the first step because there is no subject who always chooses Option B.

[21] Observe that all subjects who behave inconsistently —that is, they switch at least once from lottery B to lottery A— had to be eliminated from our analysis at this point. According to our data, the average switching point is 6.47 in GS_u,

rankings for high switching points are likely to be determined by only few subjects. Indeed it turns out that in each treatment, less than ten subjects have a switching point in the paired lottery choice phase of at least 9. To minimize this problem and to provide a clear visual representation, we opted for pooling the data of all three payoff constellations.

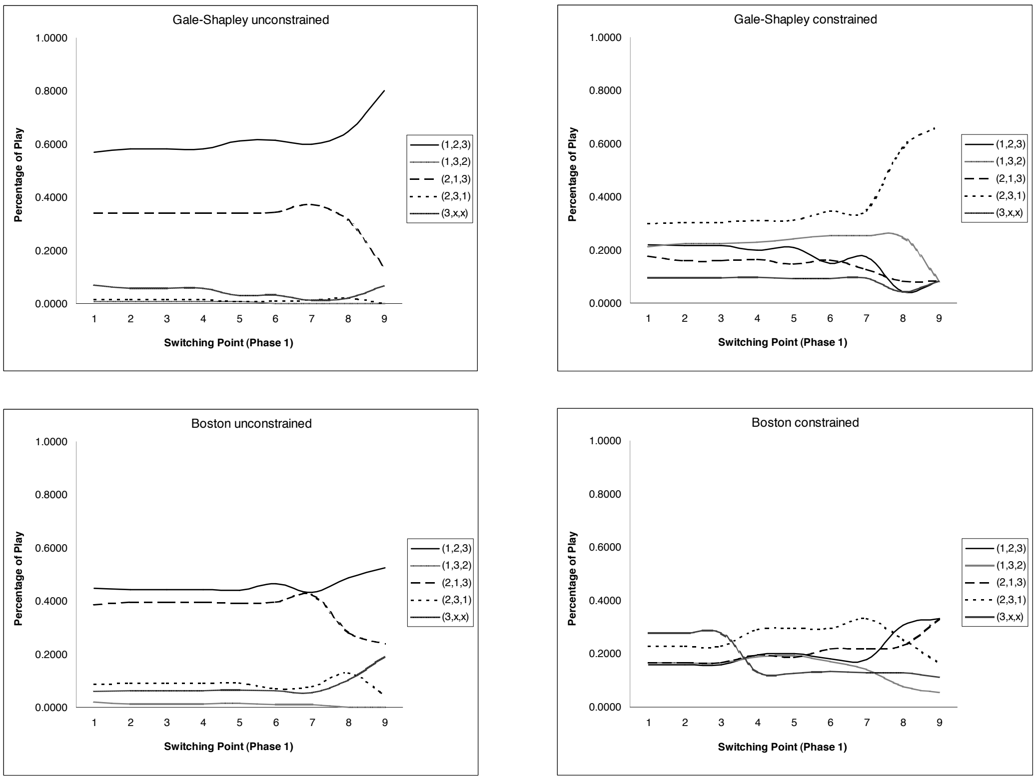

Figure 1: The distribution of submitted rankings for all four mechanisms as the subjects with lowest degree of risk aversion are eliminated step–by–step from the subject pool. We took the average over all payoff constellations.

We now discuss the graphs for each of the four mechanisms. Intuitively, the figure should be looked at in the following way: If a curve is flat, then the use of that particular strategy in that particular mechanism does not depend on the degree of risk aversion. On the other hand, if a curve is increasing (decreasing), then the corresponding strategy is used more (less) by the subjects with a higher degree of risk aversion. Our first general observation is that all curves are flat until a switching point of 7 in the paired lottery choice phase.

It can be seen in Table 4 that, in treatment GS_u, subjects predominantly say the truth or play

5.98 in GS_c, 6.70 in BOS_u, and 6.55 in treatment BOS_c. Since the actual treatment subjects participate in is exogenous from their point of view, the differences in the average switching points should not be significant. Mann Whitney U tests show that this is indeed the case.

the strategy (2,1,3). Truth–telling is the unique protective strategy for this mechanism (Proposition 2) and we indeed see that it is played considerably more often among the highly risk averse subjects. For example, the percentage of truth–telling increases from 0.6000 for a switching point of 7 to 0.8000 if the selected switching point is 9, while the corresponding percentage for (2,1,3) decreases from 0.3733 to 0.1300. The graph for treatment GS_c also provides clear evidence in favor of our hypothesis that subjects with a higher degree of risk aversion play "safer" strategies more frequently. In this treatment, the use of the protective strategy (2,3,1) increases from 0.3492 for a switching point of 7 to 0.6667 if the selected switching point is 9. The curve for (1,3,2), the second protective strategy is initially increasing and decreases sharply for switching points higher than 8. The curves for the remaining three strategies, on the other hand, are downward sloping.

Our findings for the Boston mechanism are more mixed. In treatment BOS_u, subjects mainly submit either of the protective rankings (1,2,3) and (2,1,3), and, among the two, the highly risk averse subjects rather tend to say the truth. The main difference with respect to GS_u is that the dominated rankings (2,3,1) and (3,×,×) are now also submitted to some lesser extent, and the graph shows that the highly risk averse subjects use more often the "safety" strategy (3,×,×) and less often the strategy (2,3,1) than their co–players. Finally, in treatment BS_c, all five strategies are submitted independently of the degree of risk aversion and it is difficult to identify any clear pattern. If anything, the strategies (1,2,3) and (2,1,3) are played more and the strategies (1,3,2), (2,3,1), and (3,×,×) are played less by the highly risk averse subjects. In any case, our hypothesis that the unique protective strategy (3,×,×) will be played more often by the subjects with high risk aversion cannot be validated.

The previous general discussion is now complemented with an econometric analysis. In particular, we regress the probability with which a particular ranking is submitted (again the pooled data for all three payoff constellation is considered) on a constant and the switching point extracted in the first phase of the experiment.[22] The parameter estimates of the Tobit Maximum Likelihood estimation procedure for the switching point are presented in Table 8. The errors are robust to heterogeneity.

[22] Table 12 in Appendix B contains the results of Probit Maximum Likelihood estimations on the decision of whether or not to submit a particular ranking for a given payoff constellation. In these estimations, we took into account the sequential play of the three matching markets by controlling for earlier decisions. For example, in the estimations related to truth–telling in the situation GS_{u27}, we added whether the subject told the truth in GS_{u20} and GS_{u13} as additional explanatory variables.

Mechanism	Rankings					Observations
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)	
Gale–Shapley unconstrained	0.0587**	−0.0033	−0.0056	−0.0021	−0.0474**	48
	(0.0269)	(0.0034)	(0.0263)	(0.0065)	(0.0215)	
Gale–Shapley constrained	−0.0330	0.0263*	−0.0332	0.0448**	−0.0048	49
	(0.0238)	(0.0173)	(0.0247)	(0.0251)	(0.0119)	
Boston unconstrained	0.0083	−0.0166**	0.0001	−0.0027	0.0108	51
	(0.0270)	(0.0099)	(0.0267)	(0.0156)	(0.0181)	
Boston constrained	0.0012	−0.0332*	0.0369*	0.0087	−0.0137	48
	(0.0307)	(0.0188)	(0.0225)	(0.0240)	(0.0221)	

Table 8: Tobit ML estimation results on how risk aversion affects behavior in the matching market. Standard errors are in parentheses. Errors are robust to heteroskedasticity. * Significant at the 10–percent level. ** Significant at the 5–percent level. *** Significant at the 1–percent level. OLS estimations yield similar results.

Table 8 confirms to a large extent the intuition from Figure 1. In the two treatments related to the Gale–Shapley mechanism, the protective strategies are played more often the more risk averse the subjects are.[23] All other strategies are, if anything, played less often in these two treatments. With respect to the two treatments using Boston, we find that risk aversion is uncorrelated with the use of the protective strategies. Still, some of the other strategies are correlated to the switching point. In particular, the ranking (1,3,2) is submitted less often by the highly risk averse (both in BOS_u and BOS_c), while the strategy (2,1,3) is played more often in BOS_c.

Result 5 (Risk aversion: empirical distribution of rankings.) *Subjects who are more risk averse are more likely to play a protective strategy under the Gale–Shapley but not under the Boston mechanisms.*

Finally, we analyze the implications of Result 5 for efficiency and stability and ask whether subjects with different degrees of risk aversion react differently to changes in cardinal preferences. We investigate this by dividing the subject pool of each treatment into two groups according to when the subjects switch from lottery A to lottery B in the paired lottery choice phase. The first group, which we will label as the "high risk aversion" subjects, consists of the individuals who switched in or later than the seventh decision situation. The other individuals switched in or before the sixth decision situation and are labeled as the "low risk aversion" subjects.[24]

[23]It is interesting to see that in GS_u, the highly risk averse are more likely to tell the truth and less likely to report the ranking (3,×,×). One possible explanation for this is that risk aversion is correlated with regret, which is minimized by being honest about one's own preferences.

[24]The common switching point has not been chosen arbitrarily. According to our data, the average switching point is 6.47 in GSu, 5.98 in GSc, 6.70 in $BOSu$, and 6.55 in treatment $BOSc$ so that the difference in the group sizes is minimal if the

Mechanism	Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
Gale–Shapley unconstrained					
20 ECU	**0.5200**	0.0000	0.4400	0.0000	0.0400
	0.5652	0.0000	0.3478	0.0000	0.0870
13 ECU	**0.8000**	0.0000	0.2000	0.0000	0.0000
	0.5652	0.0435	0.1739	0.0000	0.2174
27 ECU	**0.4800**	0.0000	**0.4800**	0.0400	0.0000
	0.4783	0.0000	0.3913	0.0435	0.0870
Gale–Shapley constrained					
20 ECU	0.2381	0.1905	0.0952	**0.3810**	0.0952
	0.2500	0.1786	0.1786	**0.2857**	0.1071
13 ECU	0.0952	**0.4286**	0.0952	0.2381	0.1429
	0.2500	**0.2500**	0.1071	**0.2500**	0.1429
27 ECU	0.1905	0.1429	0.1905	**0.4286**	0.0476
	0.2500	0.1071	**0.3571**	0.2500	0.0357
Boston unconstrained					
20 ECU	0.3000	0.0333	**0.4667**	0.1667	0.0333
	0.5000	0.0000	0.3500	0.1500	0.0000
13 ECU	**0.7000**	0.0000	0.1667	0.0333	0.1000
	0.5500	0.1000	0.1500	0.1000	0.1000
27 ECU	0.3000	0.0000	**0.6333**	0.0333	0.0333
	0.3500	0.0000	**0.5000**	0.0500	0.1000
Boston constrained					
20 ECU	0.2308	0.1538	0.1538	**0.3846**	0.0770
	0.3636	0.2273	0.0909	0.0909	0.2273
13 ECU	0.1923	**0.2692**	0.1154	0.1923	0.2308
	0.1818	**0.4091**	0.1364	0.1364	0.1365
27 ECU	0.1154	0.0000	0.3846	**0.4231**	0.0769
	0.1364	0.0909	0.2273	**0.4545**	0.0910

Table 9: Probability distribution of the submitted rankings for the high and the low risk averse subjects. The probabilities for the high risk averse subjects are always presented on top of the probabilities for the low risk averse subjects. The most salient rankings for each group are highlighted in boldface.

Table 9 presents the probability distributions for the two groups under consideration. To analyze the relation between risk aversion and cardinal preferences, we now apply Mann Whitney U tests. The corresponding data is presented in Table 10, which should be read as follows. Consider for example the element in the first row and the (2,1,3) column, which equals 0.0661. This value can be obtained from Table 9 by calculating the difference between how the subjects with the high risk aversion ($0.4400 - 0.2000 = 0.2400$) and how the subjects with the low risk aversion ($0.3478 - 0.1739 = 0.1739$) change

seventh decision situation is taken as the dividing line. As a consequence, the group of high risk averse players consists of 25 subjects in treatment GSu, 21 subjects in treatment GSc, 31 subjects in treatment $BOSu$, and 26 subjects in treatment $BOSc$. The respective numbers for the group of low risk averse players are 23, 28, 20, and 22. Also observe that all subjects who behave inconsistently —that is, they switch at least once from lottery B to lottery A— had to be eliminated from our analysis at this point. Finally, since the actual treatment subjects participate in is exogenous from their point of view, the differences in the average switching points should not be significant. Mann Whitney U tests show that this is indeed the case.

the use of the strategy (2,1,3) when the payoff of the second school is reduced from 20 to 13 ECU: $0.2400 - 0.1739 = 0.0661$ (*i.e.*, the difference from the high risk aversion group minus the difference from the low risk aversion group). Consequently, Table 10 indicates by how much the high risk averse subjects adapt their behavior in comparison to the low risk averse subjects as cardinal preferences vary.

Mechanism	Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
20 ECU - 13 ECU					
Gale–Shapley unconstrained	**-0.2800**	0.0435	**0.0661**	0.0000	0.1705
Gale–Shapley constrained	0.1429	**-0.1667**	-0.0714	0.1071	-0.0119
Boston unconstrained	**-0.3500**	0.1333	**0.1000**	**0.0833**	**0.0333**
Boston constrained	-0.1434	**0.0664**	0.0839	0.2378	-0.2448
20 ECU - 27 ECU					
Gale–Shapley unconstrained	-0.0470	0.0000	0.0035	0.0035	0.0400
Gale–Shapley constrained	0.0476	0.0238	**0.0833**	-0.0833	0.0238
Boston unconstrained	-0.1500	0.0333	**-0.0167**	0.0333	0.1000
Boston constrained	**-0.1119**	**0.0175**	**-0.0944**	**0.3252**	-0.1364

Table 10: Differences in the probability changes between the group of individuals with a high degree of risk aversion and the group of subjects with a low degree of risk aversion. (See the text for an interpretation of the numbers.) The shifts that turned out significant for the whole population are highlighted in boldface.

Three of the shifts in behavior that turned out significant for the whole population are primarily caused by different attitudes towards risk. *First*, the subjects with the high risk aversion tell the truth with probability 0.5200 in GS_{u20} and with probability 0.8000 in GS_{u13}. Consequently, a decrease in the monetary payoff of school 2 causes these subjects to increase the level of truth–telling by 28 %. On the other hand, the subjects with the low risk aversion tell the truth with probability 0.5600 in both GS_{u20} and GS_{u13}. This allows us to conclude that the high risk aversion subjects are responsible for the increase in the level of truth–telling in treatment GSu as the payoff of school 2 decreases from 20 to 13 ECU ($p = 0.0315$). *Second*, it can be seen from Table 9 that the same effect occurs in BOS_u. A decrease of the payoff of the second school induces the subjects with a high risk aversion to increase their level of truth–telling from 0.3000 to 0.7000, the corresponding change for the subjects with a low risk aversion is $0.5500 - 0.5000 = 0.0500$ (so that the difference–in–difference is 0.3500). Since this difference is significant ($p = 0.0373$), it is again the more risk averse subjects who are responsable for the overall effect. *Third*, an increase in the payoff of the second school from 20 to 27 ECU makes individuals play more often the strategy (2,3,1) in BOS_c. Looking back at Table 4, we indeed see that the use of this strategy increases from 0.2545 to 0.4364. This result is caused by the subjects with a low risk aversion as they increase the use of that particular strategy by about 36 % from only 0.0909 to 0.4545. The crucial point is that the high risk aversion subjects are not so responsive to that change in cardinal preference because the strategy (2,3,1) is already the most played one when the payoff of the second school is 20 ECU. Indeed, this subgroup plays the strategy (2,3,1) with probability 0.3846 before and with probability 0.4231 after the change of payoffs. The difference between the two subgroups is significant at $p = 0.0298$.[25]

Clearly, these shifts in behavior have noteworthy consequences in terms of efficiency. Given the proportion of highly risk averse subjects that reveal their true preferences under GS_u and BOS_u when the payoff of school 2 is 13 ECU, the expected average payoff per teacher, contained in Table 11, reaches its highest levels in these treatments. On the other hand, the behavior of the highly risk averse subjects is also mostly responsible for the ranking of the two mechanisms. In fact, higher levels of truth–telling under GS_u by the highly risk averse for every payoff constellation explain the efficiency advantage of GS_u over BOS_u. Imposing a limited length on submittable preferences decreases efficiency within both subgroups. Moreover, since under GS_u efficiency generally attains higher levels among the highly risk averse than among the low risk averse, while the opposite happens under GS_c, the negative impact of the constraint is particularly important within the group of the highly risk averse.

Finally, some remarks on how stability is affected by the degree of risk aversion are due. The relevant numbers are also presented in Table 11. In general, the differences in the percentage of stable matchings obtained within each group of subjects follow roughly the same rules as those obtained when the full sample is considered. Two points are worth noticing, though. *First*, the levels of stability under the unconstrained mechanisms are higher among the highly risk averse subjects, reaching 100 % under GS_u when the second school is worth 13 and 27 ECU. *Second*, as previously noted for efficiency, the constraint reduces stability and this impact under the Gale–Shapley mechanism is more substantial within the highly

[25] In some instances, a change in cardinal preferences did not induce an overall effect in behavior but, nevertheless, the difference between the two subgroups is significant as they respond in a different direction to the change in payoffs. Decreasing the payoff from 20 to 13 ECU leads to a significant difference between the two subgroups for strategy (1,3,2) in BOS_u ($p = 0.0292$), for strategy (2,3,1) in BOS_c ($p = 0.0338$), and for strategy (3,×,×) in GSu ($p = 0.0204$) and BOS_c ($p = 0.0251$). Similarly, increasing the payoff from 20 to 27 ECU leads to a significant difference between the two subgroups for strategy (2,3,1) in BS_u ($p = 0.0377$).

Mechanism	Efficiency			Stability		
	20 ECU	13 ECU	27 ECU	20 ECU	13 ECU	27 ECU
Gale–Shapley unconstrained	21.3594	25.1200	21.1059	0.8894	1.0000	1.0000
	21.5916	20.8209	20.7826	0.7824	0.5922	0.7931
Gale–Shapley constrained	17.2544	17.1442	17.7877	0.6016	0.4850	0.6814
	17.7253	17.4331	19.1358	0.5414	0.4938	0.6918
Boston unconstrained	20.2667	23.0801	20.2215	0.7027	0.4700	0.7274
	21.2500	22.2263	20.0962	0.6250	0.4641	0.5601
Boston constrained	17.9555	16.7142	18.7713	0.4374	0.3039	0.7623
	18.6199	19.1208	17.5062	0.3235	0.3230	0.5445

Table 11: Expected average payoff per teacher in ECU (to the left) and probability of stable matchings (to the right) for the high and the low risk averse subjects for every possible payoff of school 2. The values for the high risk averse subjects are always presented on top of the values for the low risk averse subjects. To be able to compare the efficiency for different cardinal preferences, we normalized the payoff of school 2 to 20 ECU independently of its actual value.

risk averse.

Result 6 (Risk aversion: efficiency and stability.) *GS_u outperforms BOS_u only for the subgroup of highly risk averse subjects. Also, for both subgroups, BOS_c does not necessarily outperform GS_c. Finally, the negative impact on efficiency and the percentage of stable matchings of a constraint on submittable preferences under the Gale–Shapley mechanism is stronger within the highly risk averse subjects.*

7 Concluding Discussion

In this paper, we have studied how cardinal preferences, *i.e.*, relative preference intensities, and risk aversion affect individual behavior in a stylized experimental matching market. The clearest lesson is perhaps that cardinality is important in that it may shape individual behavior and, in turn, affect both efficiency and stability of the mechanisms.[26] In this respect, the Gale–Shapley mechanism appears to be more robust to changes in preference intensities or, to phrase this as in Abdulkadiroğlu, Che, and Yasuda [1], the Boston mechanism induces agents to reveal their cardinal preferences more often.

A second contribution of the present study to the ongoing debate on Gale–Shapley *vs.* Boston is related to risk aversion. It is widely accepted that individual participants in a market try to manage risk in ways that affect the market as a whole. Matching markets are no exception. Our results show that which mechanism excels in efficiency terms depends on the risk aversion mix of the pool of agents. One

[26] Abdulkadiroğlu, Che, and Yasuda [1] and Miralles [20] already recognize the importance of cardinal preferences when schools' priorities are not strict. What the results of this experiment add to this is that cardinality matters, even with strict priorities.

reason for this lies in the fact that the Gale–Shapley mechanism fosters the use of "safe" strategies by the highly risk averse. In fact, we observe that there is a clear tendency for highly risk averse agents to resort to protective strategies under this mechanism.[27] Also, risk aversion is important when it comes to the evaluation of the constraint on submittable lists. Calsamiglia *et al.* [9] showed that introducing a constraint is detrimental to the performance of the mechanisms. Our results suggest that, under the Gale–Shapley mechanism, this negative impact especially affects the highly risk averse.

All this serves as a word of caution for experimentalists (when considering new designs) and theorists (when constructing new models) both alike, but perhaps more importantly, it should be taken into account by market designers as our results unveil additional dimensions in which the Gale–Shapley and Boston mechanisms can be compared. One of our results shows that the distribution of submitted strategies does not depend on whether the Gale–Shapley or the Boston mechanism is used, nevertheless it also turns out that Gale–Shapley is more efficient and more stable than Boston in the unconstrained setting independently of the considered subject pool and independently of the preference intensity. Hence, Gale–Shapley is to be preferred for "small" markets where it is no burden for the participants to rank all schools. Our message is different if the market is "large", in the sense that it is unfeasible for the parents to rank all schools, and a constrained mechanism has to be implemented necessarily. Now, the Boston mechanism performs better in terms of efficiency not only for the whole subject pool (for all preference intensities) but also within the more homogeneous subgroups (for some preference intensities). Gale–Shapley is still more stable and, therefore, the ultimate decision of which mechanism to choose in the constrained setting depends on whether efficiency or stability is considered more relevant.

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Appendix A: Sample Instructions (Translated from Spanish)

Welcome

Dear participant, thank you for taking part in this experiment. It will last at most 90 minutes. If you read the following instructions carefully, you can – depending on your decisions – earn some more money in addition to the 3 Euro show-up fee, which you can keep in any case. In order to ensure that the experiment takes place in an optimal setting, we would like to ask you to abide to the following rules during the whole experiment:

- do not communicate with your fellow students!
- do not forget to switch off your mobile phone!
- read the instructions carefully. If something is not well explained or you have any question now or at any time during the experiment, then ask one of the experimenters. Do, however, not ask out loud, raise your hand instead. We will clarify questions privately.
- you may take notes on this instruction sheet if you wish.
- after the experiment, remain seated till we paid you off.

If you do not obey the rules, the data becomes useless for us. In that case, we will have to exclude you from this experiment and you will not receive any compensation. Also, note that all participants receive the same instructions.

The Experiment

This experiment consists of two phases. Now, we will only introduce the first phase. Once it has finished, we are going to explain the second phase. However, always remember the following very important points:

1. The two phases take place in a completely anonymous setting. So, you will neither know nor learn whom you are playing with.
2. You will only be paid for phase 1 or phase 2, but not for the combined results. At the end of the whole experiment, the participant playing at terminal 9 will determine which phase is payoff relevant by throwing a coin.
3. You will not receive any feedback about your decision or the decision of your co-players until the very end of the experiment.

4. We will not speak of Euro during the experiment, but rather of ECU (experimental currency units). Your whole income will first be calculated in ECU. At the end of the experiment, the total amount you have earned will be converted to Euro. We will always indicate the exchange rate between ECU and Euro.

The First Phase

First we introduce you to the basic decision situation. Then, you will learn how the experiment is conducted. Note that if phase 1 is randomly selected for payment, then you will receive **4 Euro** for every **ECU** earned during this phase.

The First Decision Environment

In the first phase of the experiment, your basic task is to choose several times between two lottery tickets that are denoted *Option A* and *Option B*, respectively. In particular, lottery ticket A gives you a monetary payoff of x_A ECU with probability $p_x(A)$ and a monetary payoff of y_A ECU with the remaining probability $p_y(A) = 1 - p_x(A)$. Similarly, lottery ticket B gives a you a monetary payoff of x_B ECU with probability $p_x(B)$ and a monetary payoff of y_B ECU with probability $p_y(B) = 1 - p_y(B)$. As a simple example consider the lottery ticket A which is such that *you get 5 ECU in 3 out of 10 cases and 10 ECU in 7 out of ten cases.* Then, $x_A = 5.00$ ECU, $p_x(A) = 0.3$, $y_A = 10.00$ ECU and $p_y(A) = 0.7$.

The First Experiment

The first phase includes the basic decision environment just described to you. In total, there are ten pairs of lottery tickets; so, you have to make ten choices. In all ten situations, monetary payoffs are such that $x_A = 2.00$ ECU, $x_B = 3.85$ ECU, $y_A = 1.60$ ECU, and $y_B = 0.10$ ECU. However, the probabilities with which you are going to get each prize change across situations. The following figure shows the computer screen you are going to encounter during the experiment.

The computer screen presents all ten situations simultaneously with the lottery ticket A to the left of lottery ticket B. For example, in situation number 4 lottery ticket A gives you *2.00 ECU in 4 out of 10 cases and 1.60 ECU in 6 out of 10 cases.* You choose between the lottery tickets by clicking the desired option on the right hand side of the screen. Once you have made all ten choices, click on the button "Continue".

round

1

remaining time [sec]: 496

Situations	Option A	Option B	Your Choice
Situation 1	in 1 out of 10 cases you get 2.00 ECU and in 9 out of 10 cases you get 1.60 ECU	in 1 out of 10 cases you get 3.85 ECU and in 9 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 2	in 2 out of 10 cases you get 2.00 ECU and in 8 out of 10 cases you get 1.60 ECU	in 2 out of 10 cases you get 3.85 ECU and in 8 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 3	in 3 out of 10 cases you get 2.00 ECU and in 7 out of 10 cases you get 1.60 ECU	in 3 out of 10 cases you get 3.85 ECU and in 7 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 4	in 4 out of 10 cases you get 2.00 ECU and in 6 out of 10 cases you get 1.60 ECU	in 4 out of 10 cases you get 3.85 ECU and in 6 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 5	in 5 out of 10 cases you get 2.00 ECU and in 5 out of 10 cases you get 1.60 ECU	in 5 out of 10 cases you get 3.85 ECU and in 5 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 6	in 6 out of 10 cases you get 2.00 ECU and in 4 out of 10 cases you get 1.60 ECU	in 6 out of 10 cases you get 3.85 ECU and in 4 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 7	in 7 out of 10 cases you get 2.00 ECU and in 3 out of 10 cases you get 1.60 ECU	in 7 out of 10 cases you get 3.85 ECU and in 3 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 8	in 8 out of 10 cases you get 2.00 ECU and in 2 out of 10 cases you get 1.60 ECU	in 8 out of 10 cases you get 3.85 ECU and in 2 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 9	in 9 out of 10 cases you get 2.00 ECU and in 1 out of 10 cases you get 1.60 ECU	in 9 out of 10 cases you get 3.85 ECU and in 1 out of 10 cases you get 0.10 ECU	Option A Option B
Situation 10	in 10 out of 10 cases you get 2.00 ECU and in 0 out of 10 cases you get 1.60 ECU	in 10 out of 10 cases you get 3.85 ECU and in 0 out of 10 cases you get 0.10 ECU	Option A Option B

CONTINUE

If it happens that phase 1 is randomly selected for payment, one of the ten pairs of lotteries is randomly selected by the computer (each pair is selected with the same probability). Given this random draw, your payoff is then determined by using the lottery you have chosen in that particular situation. For example, if situation 9 is randomly selected and you have chosen option A in that case, then you get 2 ECU with probability 0.9 and 1.6 ECU with probability 0.1. Finally, please answer the question below. Once ready, please raise your hand.

QUESTION: Suppose lottery ticket A is such that it gives you 3 ECU with probability 0.7 and 1 ECU with probability 0.3. Similarly, lottery ticket B gives you 3 ECU with probability 0.7 and 2 ECU with probability 0.3. Which option do you choose? __________

The Second Phase

First we introduce you to the basic decision situation. Next, you will find control questions that help you to understand the situation better. Finally, you will learn how the experiment is conducted. Note that if phase 2 is randomly selected for payment, then you will receive **40 Eurocents** for every **ECU** earned during this phase.

The Second Decision Environment

The basic decision environment in the second phase of the experiment is as follows: There are three teachers —let us call them teacher 1, teacher 2, and teacher 3— who are looking for a new job. There are three schools in town (denoted X, Y, and Z) and every school happens to have one open teaching slot. Since the schools turn out to differ in their location and quality, teachers have different opinions of where they want to teach. The desirability of schools in terms of location and quality is expressed in the following table:

	Teacher 1	Teacher 2	Teacher 3
Most preferred school	X	Y	Z
Second most preferred school	Y	Z	X
Least preferred school	Z	X	Y

Schools when offering positions consider the quality of each applicant and the experience they have. On this basis, they build a priority ordering where all teachers are ranked. The following table summarizes the priority ordering of each school.

	School X	School Y	School Z
Best candidate	2	3	1
Second best candidate	3	1	2
Worst candidate	1	2	3

To decide which teacher gets offered a position at which school, teachers are first asked to submit their ranking of schools; that is, they have to indicate at which school they would like to work most, at which school they would like to work second most, and at which school they would like to work least. Observe that teachers can indicate whatever ranking they like, it does not have to coincide with the actual preferences. Given the submitted rankings, the following mechanism is used to assign teachers to schools:

1. Every teacher applies to the school she/he ranked first.
2. Each school temporarily accepts the applicant with the highest priority and rejects all other applicants.
3. Whenever a teacher is rejected at a school, an application is sent to the next highest ranked school.
4. Whenever a school receives new applications (from teachers that have been rejected in a previous round by other schools), these applications are considered together with the previously retained application. Among the previously retained application (if any) and new applications, the applicant with the highest priority is temporarily accepted, all others are rejected.
5. This process is repeated until no more applications can be rejected, and the allocation is finalized. Each teacher is assigned the position at the school that holds her/his application at the end of the process.

Example

Before we explain how the experiment is conducted, we would like to ask you to go over the following example. It helps illustrating how the allocation mechanism works. Once ready, please raise your hand, and one of the experimenters will check your answers. In case of questions, please contact any experimenter as well.

In the example, there are three teachers (1,2, and 3) and three schools (A, B, and C) who have one teaching position each. Suppose that the *submitted* school rankings are as follows:

	Teacher 1	Teacher 2	Teacher 3
1st ranked school	B	C	B
2nd ranked school	C	A	C
3rd ranked school	A	B	A

Also, suppose that the priority orderings of the schools are given by the following table:

	School A	School B	School C
1st ranked teacher	2	2	1
2nd ranked teacher	3	1	3
3rd ranked teacher	1	3	2

Please, answer the following questions:

1. In the first round of the mechanism, every teacher applies to the school she/he ranked first; that is, teacher 1 applies to school ______ , teacher 2 applies to school ______ , and teacher 3 applies to school ______ . Given these applications, every school temporarily accepts the applicant with the highest priority and rejects all other teachers. Hence, school B retains teacher ______ and rejects teacher ______ , while school C retains teacher ______ .

2. In the second round, all teachers rejected in the first round apply to the school they ranked second; that is, teacher 3 applies to school ______ . Now, schools compare the new applicants with the previously retained teachers. As a consequence, school C retains teacher ______ and rejects teacher ______ .

3. In the third round, the teacher that got rejected in the second round applies to the next highest ranked school. Hence, teacher ______ applies to school ______ . Since this school has still a free place all teachers are assigned to a school and the mechanism stops.

4. The final allocation of teachers to school is therefore as follows:

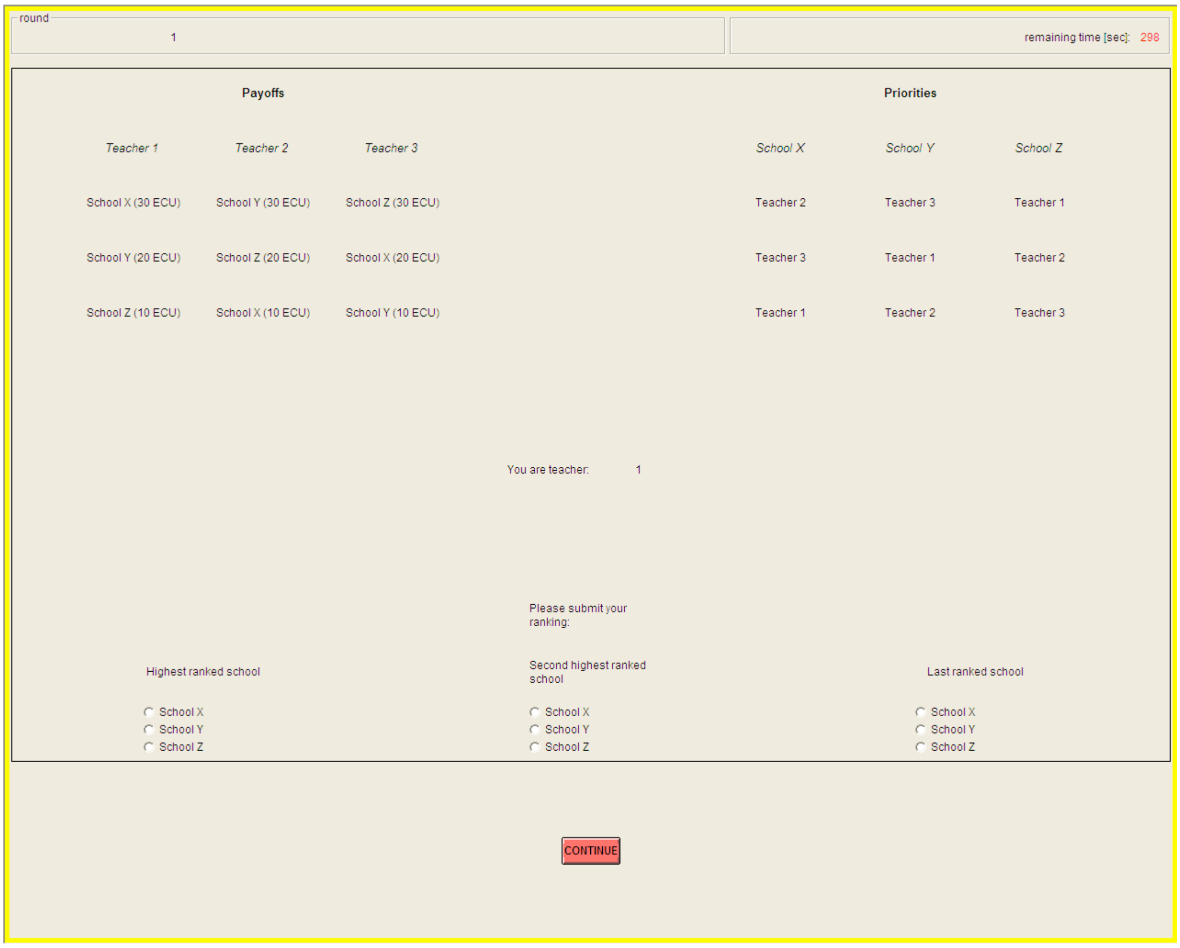
   - Teacher ______ gets a job at A.
   - Teacher ______ gets a job at B.
   - Teacher ______ gets a job at C.

The Second Experiment

In the beginning of the second phase, the computer randomly divides the participants into groups of 3. Participants within the same group will only play among themselves. The assignment process is random and anonymous, so no participant will know who is in which group. Then, each participant in a group gets randomly assigned the role of a teacher in such a way that one group member will be in the role of teacher 1, another group member will be in the role of teacher 2, and the final group member will be in the role of teacher 3. Neither the division of participants into groups nor the assignment of roles within groups is going to change during the second phase.

The basic decision situation explained above will be played three times with varying payoffs. In what follows, we will only explain the first payoff constellation in detail, the remaining two situations have a similar structure. In particular, the first payoff constellation is such that you receive 30 ECU if you end up at the **school you prefer most**, 20 ECU if you are assigned to your **second most preferred**

school, and 10 ECU if you get a job at the **school you prefer least**. To clarify how the experiment proceeds, we will present next the computer screen you are going to encounter during the experiment.



On the top of the screen, we remind you of the preferences of the teachers over schools together with the material consequences and the priorities of schools over teachers. Below you see that you are assigned the role of teacher 1. Consequently, your payoff is highest if you end up working at school X, it second highest if you work at school Y, and it is lowest if you finally get a job at school Z.

At the bottom of the screen, you are asked to submit a ranking of schools. Remember that you are allowed to submit any ranking you want. On the left hand side you indicate the school that you rank first, in the middle you indicate the school you rank second, and to the right hand side you indicate the school you rank last. The submitted rankings are then used by the computer to determine (by means of the mechanism presented before) the final assignment of teachers to schools.

Finally, observe that if the second phase is randomly chosen to be payoff relevant, then the computer is going to determine randomly one of the three situations for payment (every situation is randomly selected with the same probability). Also, note that you will never receive any feedback about decisions until the very end of the experiment. Please answer the following final question. Once ready, please raise your hand.

QUESTION: Suppose that you prefer school X over school Y over school Z. Assume also that you submit the following ranking of schools: X is ranked higher than Z, which, in turn, is ranked higher than Y. Using the same payoffs in ECU as in the example on the computer screen above, what will be your final payoff if you finally end up working at school Y?

ANSWER: ______ ECU.

Appendix B: Probit ML Estimation Results

Treatment	Rankings				
	(1,2,3)	(1,3,2)	(2,1,3)	(2,3,1)	(3,×,×)
GS_{u20}	0.0795		0.0163		−0.2194
	(0.1019)		(0.1011)		(0.2246)
GS_{u13}	0.3165***	−0.2165***	0.0187		−0.6115***
	(0.1209)	(0.0930)	(0.1069)		(0.2254)
GS_{u27}	0.0779		−0.0984	−0.0687	−0.0639
	(0.1110)		(0.1130)	(0.1938)	(0.1400)
GS_{c20}	0.0043	0.0742	−0.2545**	0.2192**	−0.1392
	(0.0949)	(0.0874)	(0.1186)	(0.1000)	(0.1209)
GS_{c13}	−0.2545***	0.1359*	−0.0187	0.0295	0.0833
	(0.0986)	(0.0920)	(0.1113)	(0.1216)	(0.1086)
GS_{c27}	−0.1500*	0.0541	0.1143	0.0317	−0.0133
	(0.1049)	(0.1004)	(0.1156)	(0.1164)	(0.0895)
BOS_{u20}	−0.0552	0.0514	−0.0335	0.0735	0.5424***
	(0.1100)	(0.0424)	(0.1034)	(0.1222)	(0.1704)
BOS_{u13}	0.1949**	−0.7892***	−0.0188	−0.2290*	0.0183
	(0.1121)	(0.1444)	(0.1159)	(0.1418)	(0.1462)
BOS_{u27}	0.0352		0.0924	−0.1227	−0.0069
	(0.1153)		(0.1179)	(0.1282)	(0.1693)
BOS_{c20}	−0.0564	−0.1179	0.0850	0.2496**	−0.2476*
	(0.1241)	(0.0986)	(0.1661)	(0.1207)	(0.1722)
BOS_{c13}	0.0046	−0.1086	0.0942	−0.1684	0.1451
	(0.1284)	(0.1231)	(0.1304)	(0.1609)	(0.1498)
BOS_{c27}	0.1736	−0.1907***	0.2034*	−0.1538	−0.2656*
	(0.1578)	(0.1352)	(0.1285)	(0.1249)	(0.1173)

Table 12: Probit ML estimation results on how risk aversion aversion affects behavior in the matching market. In case the payoff of school 2 is 13 or 27 ECU, we controlled for the behavior in the matching markets played until that point. Errors are robust to heteroskedasticity. * Significant at the 10–percent level. ** Significant at the 5–percent level. *** Significant at the 1–percent level.