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Monkey see, monkey do: truth-telling in matching algorithms and the manipulation of others

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Abstract
We test the effect of the amount of information on the strategies played by others in the theoretically strategy-proof Top Trading Cycles (TTC) mechanism. We find that providing limited information on the strategies played by others has a negative and significant effect in truth-telling rates. Subjects report truthfully more often when either full information or no information on the strategies played by others is available. Our results have potentially important implications for the design of markets based on strategy-proof matching algorithms.

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1. Introduction

Matching theory has been extremely successful in providing algorithms used for the design of markets in the real world. One of the most important advantages of any algorithm, when it comes to its practical application, is its strategy-proofness. Indeed, if participants could be convinced of the impossibility of manipulating the mechanism they would devote their energy to discovering their own preferences, for instance, investigating which schools are best suited for them, rather than devising strategies to game the system.

There is an ongoing debate on whether strategy-proofness can be safely assumed for the real-life implementation of a matching algorithm. Early matching experimental literature (i.e., Chen and Sönmez, 2002; Chen and Sönmez, 2006)[1] suggests truth-telling rates are higher for strategy-proof mechanisms when compared to non-strategy-proof ones. This result might be driven by the fact that non-strategy-proof mechanisms used for comparison are easy to manipulate, in the sense that it is easy to find a seemingly good, or satisfactory, way to manipulate. Conversely, the low manipulation rates found for strategy-proof mechanisms may be caused not by the participants understanding of strategy-proofness, but by them being unable to find a satisfactory manipulation strategy and thus reporting a default option, the induced preference order. Guillen and Hing (2013) give some support to that idea by showing how manipulation becomes modal when wrong advice is introduced. In a similar vein, Pais and Pintér (2008) and Pais et al. (2011) find that manipulation rates increase when more information about the underlying preferences of other participants is introduced. Klijn et al. (2013) find a correlation between risk aversion and the likelihood of manipulation by choosing a “safe” (but strictly dominated) strategy under the Gale-Shapely mechanism. That is, it seems clear that the majority of participants in laboratory experiments don’t understand strategy-proofness but instead respond to changes in the environment and are somehow guided by their own risk attitudes.

These facts may be playing a role in the way real-life designed markets work and are perceived by participants. Anecdotal evidence, sometimes reflected in academic journals, indicates a worrying degree of ignorance of participants in real-world markets. Guillen and Hing (2013) cite popular blogs that encourage manipulation in the Boston Public School deferred acceptance based system. Fisher (2009) elaborates on the general dysfunctionality of

[1] Other noticeable experimental papers in the literature are Kagel and Roth (2000), Haruvy and Unver (2007), Echenique, Wilson and Yariv (2009), Featherstone and Mayefsky (2011), Featherstone and Niederle (2011), Hugh-Jones, Kurino and Vanberg (2013), Hakimov and Kesten (2014), Niederle, Roth and Unver (2013), Niederle and Yariv (2009).

the NRMP match system, Nagarkar and Janis (2012) point out the fact that "*Advisors occasionally tell* [NRMP] *applicants to realistically consider their chances of matching at a program when determining its position on their rank lists.*" Internet forums in which candidates discuss the NRMP are littered with discussions on how to game the system.

Given the evidence cited above, it is reasonable to hypothesize that the actions of participants can be influenced by the likely manipulation of other participants, as it seems to happen in both the BPS and NRMP matches. That is what we call the "monkey see, monkey do" effect. We aim to study this phenomenon in the experimental laboratory.

This paper presents an in-depth analysis of one behavioral factor affecting truth-telling in both the laboratory and real-life setting. We present a test of uncertainty about the behavior of others. That is, we study how the amount of information about the preferences actually revealed by other participants has an effect on the truth-telling rates. We control the amount of information about revealed preferences by using an individual decision making set up in which information about computer-simulated players (hereafter, computer players) is revealed to human participants. All the subjects in our experiment played a full information deterministic baseline followed by one out of four treatments with different amounts of information on the strategies of other participants: uncertain misrepresentation (UMT), in which participants know the underlying preferences of computer players, but they know that at least one of them will not report truthfully; certain blocking misrepresentation (CBMT), in which underlying preferences are known and human players are informed of a computer player misrepresenting its preferences so that the human's first preference is blocked under the assumption of the truth-telling of other computer players; certain unblocking misrepresentation (CUMT), in which one of the computer players misrepresents its underlying preferences in a way that does not affect the chances of the human player to get the top choice; and underlying preferences (UPT), in which the underlying preferences are known, but nothing about how they are reported, other than computer players will maximize their profit.

This paper is the first one to our knowledge to vary the amount of information on the strategies of other players from full information in the baseline to no information in UPT UMT, CBMT and CUMT which can be classified as limited information treatments in which the "monkey see, monkey do" effect may play a role. In contrast UPT does not give any clue as to the behavior of others. This is a no-information treatment.

The baseline allows participants to use TTC to find the best response to the perfectly known behavior of computer-simulated agents. Over 63% of the subjects report truthfully in the baseline. Truthful preference revelation decreases greatly, and significantly, in each of the limited information treatments. The certain misrepresentation of preferences by computer players irrespective of the blocking or non-blocking type increases misrepresentation rates by experimental subjects significantly relative to uncertain misrepresentation.

We cannot reject the understanding of the dominant strategy property of TTC for 31% of the subjects, as they submitted their true preference orders in the two treatments they played. Additional tests allowed us to conclude that these subjects are more likely to achieve a higher score in the Cognitive Reflection Test (Frederick, 2005) and be more successful in finding solutions to mechanism-related tasks. In contrast to Klijn et al. (2013) we find no significant difference between subjects who played optimal and defensive strategies.

The rest of the paper is structured as follows: in section 2 we justify the experimental design and treatments; while in 3 both theoretical and behavioral predictions are formulated. Section 4 presents the results followed by the concluding remarks in section 5.

2. Experimental design and procedures

We design an experiment to compare the individual decisions of participants in matching markets in the lab under the Top Trading Cycles mechanism (TTC). We use the TTC for the school choice problem with a preliminary assignment as formulated in Abdulkadiroğlu and Sönmez (2003):

"Step 1: Assign a counter for each school which keeps track of how many seats are still available at the school. Initially set the counters equal to the capacities of the schools. Each student points to her favorite school under her announced preferences. Each school points to the student who has the highest priority for the school. Since the number of students and schools are finite, there is at least one cycle. (A cycle is an ordered list of distinct schools and distinct students (s_1 , i_1, s_2,..., s_k, i_k) where s_1 points to i_1, i_1 points to s_2 .... s_k points to i_k, i_k points to s_1.) Moreover, each school can be part of at most one cycle. Similarly, each student can be part of at most one cycle. Every student in a cycle is assigned a seat at the school she points to and is subsequently removed. The counter of each school in a cycle is reduced by one and if it is reduced to zero, the school is also removed. The counters of all the other schools stay put.

In general, at **Step k:**

Each remaining student points to her favorite school among the remaining schools and each remaining school points to the student with the highest priority among the remaining students. There is at least one cycle. Every student in a cycle is assigned a seat at the school that she points to and is subsequently removed. The counter of each school in a cycle is reduced by one and if it is reduced to zero the school is also removed. The counters of all the other schools remains in place. The algorithm terminates when all students are assigned a seat. Note that there can be no more steps than the cardinality of the set of students."

We do not aim to simulate the complexity of the real-world school allocation problem, but rather to create a simple artificial environment in which to test the effect of the amount of information on the reported preferences of others. The preference profiles of participants are fixed across all treatments, as are the priorities of students in schools. An experimental subject represents one out of four students in a market. The other three students are played by the computer. We choose a small market to keep things as simple as possible. So there are four schools in the market with one slot each. The preferences of players are designed in such a way as to ensure the decisive power of the human player. A misrepresentation of preferences will cause a suboptimal outcome in all treatments but one. The priorities of students in schools are generated through the district school priority, in which each player has a priority only to the school in its own district. The preferences of students and the priorities of the school for all environments are given by:

Table 1. Priorities of students in schools

Home school	Student
A	Computer 1
B	Computer 2
C	Human
D	Computer 3

Table 2. Underlying preferences

True preferences				
	Human	Computer 1	Computer 2	Computer 3
Top choice	A	B	D	C
2nd choice	B	C	C	D
3rd choice	D	A	A	A
4th choice	C	D	B	B

This structure of the priorities and preferences is common for all five treatments. The baseline is a fully deterministic game as participants know that the computer players will send their true preferences to the clearing house. It is played by all subjects of the experiment followed by one of the other four treatments.

2.1. Treatment structure

The treatments are described below:

1. Baseline treatment. In the baseline treatment subjects know the underlying preferences and are aware that computer players submit their true preferences. The game is deterministic. Subjects know the exact inputs in the algorithm and should be able to calculate the outcome. Subjects are not required to understand strategy-proofness to behave optimally.

2. Uncertain misrepresentation treatment (UMT). In this treatment the participants are aware of the underlying preferences of the computer, but they know that at least one of the computer players did not report its preferences truthfully. They do not know the way in which the preferences were misrepresented. In this treatment subjects need a deeper understanding of the mechanism to make the optimal decision, truth-telling, as the mechanical calculation of outcomes is no longer an option.

3. Certain blocking misrepresentation treatment (CBMT). In this treatment subjects are aware of the underlying preferences of the computer players and are aware that computer player 1 submits A-B-C-D instead of its true preference B-C-A-D and other computer players behave to maximize their payoffs. This misrepresentation by computer player 1 blocks the top choice of the human player. In this treatment there is more than one payoff-maximizing strategy. As their top choice is blocked, subjects can swap their first and second preferences. Subjects with an understanding of the dominant strategy property of the TTC should not invest time in calculating the outcomes under different strategies and should still submit the true list.

4. Certain unblocking misrepresentation treatment (CUMT). In this treatment subjects are aware of the underlying preferences of the computer players. They also know that computer player 3 submits B-C-D-A instead of his true preference C-D-A-B and other computer players behave to maximize their payoff. This misrepresentation, however, does not influence the possibility of the participants getting their top choice. The only payoff-maximizing strategy in this treatment is to send the true list.

5. Underlying preferences treatment (UPT). The participants only know the underlying preferences of the computer players. They are also informed that the computer players will state their preferences in such a way so as to maximize their payoffs. This treatment is the most similar to the usual implementation of a matching experiment in an incomplete information environment.

As was previously mentioned, every subject played two treatments, the baseline plus one of the other five treatments. Subjects were asked to submit their preferences simultaneously for the two treatments they played. Only the resulting allocation of one of the treatments, randomly chosen, was payoff relevant. Subjects could express their preferences for the two treatments played by choosing 55% as the probability of their favorite treatment.[2]

2.2. Additional procedures and controls

Apart from the treatments described in the previous section, the following incentivized procedures were performed in the lab by every subject as a control:

- After reading the instructions subjects were asked to apply the TTC algorithm to solve an example of the allocation problem. Feedback was not provided until the end of the experiment. [Allocation]
- Subjects were also asked to provide answers to two multiple-choice questions about features of the TTC mechanism. [MC]
- Subjects had three minutes to provide answers to a 10-question Wonderlic cognitive ability test, (Wonderlic and Hovland, 1939). [Wonderlic]
- The well-known three-question Cognitive Reflection Test (Frederick, 2005). [CRT]
- And a risk aversion test, The Bomb Task (Crosetto and Filippin, 2013). [Risk]

[2] The vast majority of subjects chose 50-50. As the results for the rest do not give any significant cifference, we do not report the results related to this design feature.

Thus the experiment was run as follows:

1. Instructions
2. Allocation
3. MC
4. Treatments
5. Wonderlic
6. CRT
7. Risk
8. Payment

2.3. Procedures

Eight experimental sessions were run in the TU-lab of the Technical University Berlin between November 2012 and January 2013. In total, 188 experimental subjects participated in the experiment, most of whom were students at Berlin universities. Only 180 data points were used in the subsequent analysis. Eight subjects were not able to submit their ranking lists within the 10 minutes provided. The average length of the session was 80 minutes, and subjects earned 15.04 EUR on average.

3. Predictions

As the TTC mechanism is strategy-proof it is at least a weakly-dominant strategy to state the truth in all treatments. Note that truth-telling is not the only payoff-maximizing strategy in CBMT, as the top choice is blocked by computer players.

Hypothesis 1: Due to the strategy-proofness of TTC the participants should reveal their true preferences in all treatments.

From the previous experimental literature on matching we know that it is highly unlikely that all experiment participants will be able to follow the dominant strategy. We expect – inspired by the anecdotal evidence cited in the introduction – that the amount of information about the behavior of the other participants would be a factor explaining the misrepresentation of the preferences. Thus we state hypothesis 2 in the following way:

Hypothesis 2 [monkey see, monkey do]: Due to the deterministic nature of the baseline treatment, the rate of truthful preference revelation should be higher in the baseline than in the limited information treatments (UMT, CBMT, CUMT).

Conversely, and in line with previous literature, the absence of information on the other's reported preferences results in high truth-telling rates. Therefore:

Hypothesis 3: Due to the *absence* of information on the reported preferences of other players, the rate of truthful preference revelation should be higher in the no-information treatment (UPT) than in the limited information treatments (UMT, CBMT, CUMT).

Hypothesis 4: Truth-telling in CUMT is a strictly dominant strategy, but in CBMT it is only weakly dominant. Therefore the truth-telling rate should be lower in CBMT.

4. Results

Table 3 shows the truth-telling rates by treatments. The asterisks represent the significance level of the statistical test for the equality of proportions of the truth-telling rates in option A vs. option B.

Table 3. Truthful reporting rates by treatment

N	Treatment	Truth in Baseline	Truth in Treatment
46	UMT	0.739	0.435***
46	CBMT	0.587	0.282***
42	CUMT	0.571	0.309***
46	UPT	0.63	0.456**

Result 1: There is little support for Hypothesis 1. Misrepresentation is quite common across all treatments. The highest truth-telling rates are in the baseline treatments, where on average 63.3% of subjects report truthfully.

Even in the simplest environment with no uncertainty about the stated preferences of other participants (baseline) 36.7% of subjects fail to report truthfully. This result shows that without any additional explanation of the properties, subjects in the lab tend to misreport their preferences. It could also be evidence of the fact that the high percentage of truth-telling in the no-information matching experiments[3] (i.e., Chen and Sönmez, 2006) may be driven by the default option of truthful reporting, rather than an understanding of the incentive properties of the mechanisms (Guillen and Hing, 2013).

Result 2: Hypothesis 2 cannot be rejected. The truth-telling rates in the three limited information treatments are significantly lower than in the baseline.

The decrease in truth-telling rates from the baseline to each of the limited information treatments indicates that a high proportion of subjects who could previously be classified as behaving rationally are actually affected by the "monkey see, monkey do" effect. Irrational manipulation becomes the modal behavior across the limited information treatments.

Table 4. *p*-values for the equality of proportions test

	Baseline	UMT	CBMT	CUMT	UPT
Baseline	-	0.001	0.002	0.007	0.047
UMT	-	-	0.064	0.11	0.42
CBMT	-	-	-	0.39	0.04
CUMT	-	-	-	-	0.08
UPT	-	-	-	-	-

Result 3: There is only limited support for hypothesis 3. Although the truth-telling rate is lower in UPT than in the limited information treatments, this difference is only significant when compared to the CBMT.

Result 4: Hypothesis 4 can be rejected. There is no significant difference between the CBMT and CUMT. The blocking feature in CBMT does not seem to have behavioral implications.

One could argue that in the baseline treatment, due to the fact that the game is deterministic, rational subjects would be able to find the solution to the game just by using the algorithm. Also, as they receive the top choice in the solution, it is enough for them to state the true top choice to ensure the maximum payoff. If one considers the relevation of the true

[3] The highest truth-telling rates are found in experiments in which no information is provided about either the stated or underlying preferences.

top choice to be the sufficient truth-telling criterion, the previous results of the section become even more significant. Note, it is not sufficient to reveal the top choice only in the other treatments, as there is an uncertainty of the strategies of the other players, but in order to make a full comparison of this parameter we take an overview of the top choice revelation rates in all treatments. Table 5 shows how results 1 and 2 are still true when considering the top choice truthful revelations.

Table 5. Top choice revelation by treatment

N	Treatment	Truthful top choice in Baseline	Truthful top choice in Treatment
46	UBT	0.87	0.5***
46	CBMT	0.74	0.48***
42	CUMT	0.76	0.5***
46	UPT	0.8	0.54***

Our design allows us to characterize subjects into the following categories:

- **Dominant strategy:** Subjects who played *as if* they understood strategy-proofness. These are subjects who submitted the full true lists in both the baseline and the treatment they played.
- **Best response:** Subjects who were able to play best response to the market, but failed to report truthfully. These are subjects who did not submit full-length lists truthfully in the treatment.
- **Bias:** Subjects who played best response in the baseline, but not optimally in a limited information treatment.
- **Limited ability:** Subjects who failed to best respond (reveal at least their top choice truthfully) in the deterministic, full information baseline.

Table 6. Distribution of participants between categories

	Number of subjects	Percent of total number of participants
Dominant strategy	56	31%

Best response	34	19%
Bias	53	29%
Limited ability	37	21%

For 31% of subjects we cannot reject the understanding of the dominant strategy concept. We emphasize the relatively strong requirement for this categorization, as even in case of certainty, where only the true top choice matters for allocation, we require the full truthful list to be submitted. Additionally, 19% of subjects (50% in total, dominant strategy + best response) were able to maximize their payoffs. Most of the "best response" subjects (60%) played CBMT. Recall that in CBTM truthful preference revelation is only a weakly dominant strategy. Therefore stating the true two top choices or stating the second choice on the list both lead to the best possible payoff and allows for this categorization. If we consider the relative popularity of that kind of misrepresentation in the other treatments (a large proportion of the "bias" category), we may be overestimating the number of subjects who are actually able to best respond.

In summary, the majority of our subjects failed to understand the strategy-proofness property of TTC. A higher percentage of subjects were able to at least best respond, but markets populated by individuals like ours are likely to generate substantial inefficiency.

Other than the main experiment, subjects performed four other incentive-based tasks: Allocation, MC, Wonderlic, CRT, and Risk. In Allocation subjects had to find the solution for a market with six students competing for seats in three schools, with two seats in each school. The structure of this task is very similar to the solve example in the experimental instructions (see the Appendix for details). Subjects received 2 EUR for a correct allocation, but they only learned the result at the end of the experiment. After Allocation, subjects were asked to answer the following multiple-choice question[4] about the mechanism:

[4] In the experiment, subjects were also asked the following question:

> *The allocation procedure is constructed in such a way to guarantee students an assignment at least as good as their district school, according the ranking list: True or False*
>
> *However, we do not include the answers in our analysis, as a lot of subjects did not understand the formulation. In the post-experiment questionnaires subjects complained (those who answered false), that in fact you can get a worse school than your district school if you listed the worse school higher in the ranking lists. Thus we concluded that the question was not clearly formulated and excluded it from our analysis.*

Which of the following statements about the mechanism is correct?:

a. Before choosing what ranking to choose, students should be careful to avoid applying to the most popular school.
b. Knowing the preferences and ranking of the others is crucial for choosing your own ranking list.
c. The mechanism is constructed in such a way that the ranking list should always coincide with your true preferences.
d. You should only state your true preferences if you are certain that the other participants will also state their true preferences.

Table7. Proportion of correct answers to the direct testing of the mechanism knowledge

	Number of participants	Proportion
Correct Allocation	106	0.59
Correct MC	83	0.46
Both	48	0.27

It is somehow surprising that 46% chose the right answer to MC, but only 31% submitted the true preferences in both the baseline and treatment. In any case, only 27% of participants were able to earn the maximum payoff for both the mechanism-related tasks. On the other hand, dominant strategy players were significantly (5% significance level) more successful than the other players in those tasks. See table 8.

Table 8. Correct answers in the mechanism-related tasks by categories

Category	Percent of correct answers in both tasks
Dominant strategy	39.3%
Best response	20.0%
Other bias	21.0%
Limited ability	21.6%

After participants submitted their preferences in the main experimental task, they were given 2.5 minutes to answer the three CRT questions. Then they started a 10-question, three-minute Wonderlic test (see Appendix). No subject was able to finish 10 questions within the given time. Participants received 50 cents for answering any CRT or Wonderlic question correctly.

Table 9. The performance in intelligence connected tasks by categories.

Category	Average CRT performance	Average Wonderlic test performance
Dominant strategy	1.64	3.68
Best response	1.23	3.53
Bias	1.21	3.08
Limited ability	0.86	2.81
Average	**1.28**	**3.29**

Dominant strategy players fared significantly better than any of the other groups in CRT. Both dominant strategy and best response players fared better than the other groups in Wonderlic. On the other hand we did not find any significant difference between groups in our risk task, the so-called "bomb task" by Crosetto and Filippin (2013).

Table 10. Average number of bombs collected by category

Category	Average number of bombs collected
Dominant strategy	48.30
Best response	47.06
Bias	46.05
Certainty biased subjects	44.59
All categories together	**46.62**

We also ran logit regressions to determine the marginal effects of the determinants of behavior. Note that CRT and Wonderlic were highly correlated, so we generated the variable which is the sum of the scores in these tests.[5] Table 11 shows the marginal effects of the logit regression for the dominant strategy category dummy

Table 11. Logit regression, marginal effects

Predict (Dominant strategy category	Marginal effect

[5] We also ran two separate regressions for each of the scores with similar results (available upon request).

dummy)	
CTR+Wonderlic test score	0.038*** (0.014)
Correct answer in both mechanism-related tasks	0.20** (0.083)
Number of bombs collected	0.002 (0.02)

The standard errors are in brackets. ***- significance under 1% level, **- significance under 5% level, *-significance under 10% level.

In summary:

Result 5: Subjects are more likely to behave as if they understand the dominant strategy concept if they are successful in answering mechanism-related questions or if their CRT performance and Wonderlic test performance is higher.

5. Conclusion

The strategy-proofness of matching mechanisms is often cited as being one of the most relevant properties regarding their practical implementation. This line of thought has been even further encouraged by laboratory experiments in which the majority of subjects behaved as if they understood strategy-proofness. However, more recent experimentation indicates that the rates of truthful revelation decrease when subjects are given a certain amount of information. Other than that, our experiment is inspired by anecdotal evidence of misrepresentation in the real-life application of mechanisms such as DA and TTC. Misrepresentation may feel compelling because “everyone else does it.” This is what we call the “monkey see, monkey do” effect.

We showed that in a very simple laboratory environment the amount of information given about the reported preferences of others matters for the experimental subjects, and therefore most of them fail to understand the dominant strategy property. We also show that cleverer subjects are able to perform significantly better. There may be some room to improve the education of participants in real-world markets. For instance, particular advice taken from blogs could be used as an example to falsify. We are not, however, overly enthusiastic about the usefulness of the former policy option. After all, 21% of the subjects in our experiments were not even able to best respond to a deterministic, favorable environment. In any case, matching mechanisms are a necessity. Mechanisms with good theoretical properties like strategy-proofness may be even more adequate in most circumstances. However, out in the wild, monkey business abounds. Good properties cannot be taken for granted.

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Appendix

Instructions

This is an experiment in the economics of decision making. The instructions are simple, and if you follow them carefully and make good decisions you might earn a considerable amount of money which will be paid to you in cash at the end of the experiment. In this experiment we are going to simulate an allocation of students to schools. The procedure, payment rules, and student allocation method will be described in detail below. Please do not communicate with each other during the experiment. If you have any questions, raise your hand and the experimenter will come and help you.

***NOTE* you are welcome to use the provided scratch paper.**

Procedure

- The payment you receive will depend on the school you are allocated.

- There are four schools. Each one holds a different value to you. This will be given on your computer screen.

- You are in a group of four which includes three computers and yourself.

- In this simulated environment the computers have their own set of school values. They may or may not differ from yours.

- Your "local school" and those of the computer players will be indicated on your computer screen. A participants' local school is the one located in the district in which they live.

- After you have submitted your decision to the "Centralized authority" the computer will determine the student allocation by the following Student Allocation Method.
  ***NOTE* all schools A to D have to be included in the ranking.**

- You will have 10 minutes for the student allocation task. You may complete it at your own pace.

In this experiment there is a specific school environment in which you will take part. The details will be shown on your screen.

Each participant is first tentatively assigned to the school within her respective district. Next, Decision Sheet rankings, which are submitted to the "centralized authority," are used to determine mutually beneficial exchanges between two or more participants. The order in which these exchanges are considered is determined by a fair lottery. This means each participant has an equal chance of being the first in line, the second in line, … , as well as the last in line. The lottery will be run by computer, and no one will know the outcome of it prior to making the decision.

The specific allocation process is explained below.

1. Initially all slots are available for allocation.
2. Each student sends a Rank-list of schools to centralized allocation office, which uses the following mechanism to determine the final allocation:
   - All participants are ordered in a queue based on the order in the lottery.
   - Next, the participant at the top of the queue applies to the school of his top choice, based on her ranking list.
     i. If the application is submitted to her district school, then her tentative assignment is finalized (thus she is assigned a slot at her district school). The participant and her assignment are removed from subsequent allocations. The process continues with the next participant in line.
     ii. If the application is submitted to another school, the procedure moves as follows:

        Say applicant Claudia's home district school is school A and she is applying to school B. Then Claudia's application is submitted to school B. After that, one of the students who tentatively holds the slot at school B has to be chosen. In particular, among all these students, we choose the student who is the first in the queue. (So we follow the queue ordering while choosing among students of school B.) Then this student is moved to the top of the queue directly in front of the requester (Claudia).

- o Whenever the queue is modified, the process continues similarly: An application is submitted to the highest ranked school with available slots for the participant at the top of the queue.
  - i. If the application is submitted to her district school, then her tentative assignment is finalized. The process continues with the next participant in line.
  - ii. If the application is submitted to another school, say school *S,* then we follow the procedure explained in example with Claudia: the first participant in the queue who tentatively holds a slot at school *S* is moved to the top of the queue directly in front of the requester.

3. A mutually-beneficial exchange is obtained when a cycle of applications are made in sequence, which benefits all affected participants, e.g., I apply to Stefan's district school, Stefan applies to your district school, and you apply to my district school. In this case, the exchange is completed and the participants as well as their assignments are removed from subsequent allocations. This way, each participant is guaranteed an assignment which is at least as good as her district school based on the preferences indicated in her Rank list.
4. The process continues until all participants are assigned a school slot.

Example

In order to understand the mechanism better, let us go through a simple example together:

If you have any questions about any step of the allocation procedure please feel free to ask at any point.

There are six students (ID numbers from 1 to 6) on the market, and three schools (school A, school B, and school C) with two free slots each. Students 1 and 2 live in the district of school A, students 3 and 4 live in school district B, and, finally, student 5 and 6 live in school district C.

It means that the tentative assignments look as follows:

Tentative assignments of students (IDs)	School A	School B	School C
slot 1	1	3	5
slot 2	2	4	6

Students submitted the following school rankings in their decision sheets:

Student ID	1	2	3	4	5	6
Top choice	B	C	A	C	C	A
Middle choice	A	A	C	B	A	B
Last choice	C	B	B	A	B	C

The lottery determined the following order (student IDs): 1-2-3-4-5-6

This allocation method consists of the following steps:

Step 1. The queue looks as follows: 1-2-3-4-5-6 (the initial queue order is always determined by the lottery). Thus student 1 (the first in the order) applies to school B (her top choice). It is not her district school. The first student in the queue who tentatively holds the slot in school B is student 3. And thus the queue is modified.

Step 2. The queue looks as follows: 3-1-2-4-5-6. Thus student 3 applies to school A. This school is not her district school, but the cycle of beneficial exchange appears. Student 3 wants to attend student 1's district school, and at the same time student 1 wants to attend student 3's district school. The beneficial exchange is obtained. Allocations of students 1 and 3 are finalized and they are excluded from the queue, and also 1 slot in school A and 1 slot at school B are excluded from the allocation process.

Finalized assignments	School A	School B	School C
slot 1	3	1	-
slot 2	-	-	-

Step 3. The queue looks as follows: 2-4-5-6. Student 2 applies to school C. It is not the school of her district. The first student who tentatively holds a slot in school C is student 5. And thus the queue is modified.

Step 4. The queue looks as follows: 5-2-4-6. Student 5 applies to school C. It is her district school. Thus student 5 is assigned to school 5. Her allocation is finalized and she is excluded from the queue as well as the slot in school C.

Finalized assignments	School A	School B	School C
slot 1	3	1	5
slot 2	-	-	-

Step 5. The queue looks as follows: 2-4-6. Student 2 applies to school C again. It is not the school of her district. The first student who tentatively holds a slot in school C is now student 6. Thus the queue is modified.

Step 6. The queue looks as follows: 6-2-4. Student 6 applies to school A. This school is not her district school but the cycle of beneficial exchange appears. Student 6 wants to attend student 2's district school, and at the same time student 2 wants to go to student 6's school. The beneficial exchange is obtained. Allocations of students 2 and 6 are finalized and they are excluded from the queue, and also 1 slot in school A and school C is excluded from the allocation process.

Finalized assignments	School A	School B	School C
slot 1	3	1	5
slot 2	6	-	2

Step 7. There is only one student in the queue – student 4. She wants to apply to school C but there are no more free slots there, so she applies to her second choice – school B. It is her district school and she is assigned to the slot in school B.

Thus the final allocation of students looks as follows:

Finalized assignments	School A	School B	School C
slot 1	3	1	5
slot 2	6	4	2

End of instructions.

Mechanism related quiz:

Mechanism understanding

In order to check the level of understanding of the allocation procedure we ask you to find out the allocation of the student for the following market:

You will earn 2Eur for a correct answer.

There are six students (ID numbers from 1 to 6) on the market, and three schools (school A, school B and school C) with two free slots each. Students 2 and 3 live in the district of school A, students 4 and 5 live in the district of school B and, finally, students 1 and 6 live in the district of school C.

This means that the tentative assignment looks as follows:

Tentative assignments	School A	School B	School C
	2	4	1
	3	5	6

The lottery determined the following order (student IDs): 5-6-2-1-3-4

The students submitted their school preferences. These are given on the "Quiz – mechanism understanding" page on your computer screen.

You have 10 minutes to correctly determine the final allocation. If you have any questions raise your hand and we will come to you. However, the experimenter will not assist you with the task.

Please choose a correct answer to the multiple choice questions about mechanism. You will earn 50 cents for each correct answer.

1. The allocation procedure is constructed in a way to guarantee students an assignment which is at least as good as their home school, according the ranking list, which is submitted to the authority: True or False?
2. Which of the following statements about the mechanism are correct:
    a. Before choosing what to submit as a ranking list, students should be careful not to apply to the most popular school
    b. Knowing the preferences and ranking lists of others is crucial when choosing your own ranking list
    c. The mechanism is constructed in such a way that the ranking list should always coincide with your true preferences.

d. You should only state your true preferences if you are certain that everybody will state their true preferences.

CRT

- A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?

- If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

- In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

Wonderlic test

I need to translate it from German

Risk-aversion related task instructions

Risk aversion measure (Bomb risk task. Crosseto Fillipin, 2013)

On the next screen you will see a field composed of 100 (10*10) numbered boxes.

You can earn 5 cents for every box that is collected. Every half of a second a box is collected starting from the top-left corner. Once collected, the box disappears from the screen, and your potential earnings are updated accordingly. At any moment you can see the amount earned up to that point.

Such earnings are only potential, however, because behind **one** of these boxes a time bomb is hidden that will destroy everything that has been collected.

You do not know where the time bomb is. You only know that it can be in any place with an equal probability. Moreover, even if you collect the bomb, you will not know until the end of the experiment.

Your task is to choose when to stop the collecting process. You can do so by hitting ’Stop’ at any time.

At the end of the experiment, the computer will randomly determine the number of the box containing the time bomb.

If you happen to have collected the box in which the time bomb is located, you will earn zero. If the time bomb is located in a box that you did not collect, you will earn the amount of money accumulated before hitting 'Stop.'

Please process to the next screen to start the exercise.

Table A1. Marginal effects for logit regression

Predict(Dominant strategy category dummy)	Marginal effect
CRT performance	0.08*** (0.03)
Correct answer in both mechanism-related tasks	0.19** (0.08)
Number of bombs collected	0.002 0.002

The standard errors are in brackets. ***- significance under 1% level, **- significance under 5% level, *- significance under 10% level.

Table A2. Marginal effects for logit regression

Predict(Dominant strategy category dummy)	Marginal effect
Wonderlic test performance	0.047** (0.021)
Correct answer in both mechanism-related tasks	0.21** (0.08)
Number of bombs collected	0.002 0.002

The standard errors are in brackets. ***- significance under 1% level, **- significance under 5% level, *- significance under 10% level.