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Abstract

We report data from controlled laboratory experiments on two-sided matching markets in which participants interact in a decentralized way, without having to refer to a central clearinghouse. Our treatments have been designed to evaluate the effect of information, search costs, and binding agreements on the final outcome and also on the individual strategies that lead to it. We find that these features affect the level and pace of market activity as well as the identity of those who receive proposals. While the lack of information alone does not reduce stability or efficiency, its combination with search costs can be detrimental.

Keywords: decentralized matching, experiments, stability, two-sided matching
JEL Classification Numbers: C78, C91, D82

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1 Introduction

Many (two-sided matching) markets are decentralized in the sense that no matchmaker exists to perform the matching between the two sides of the market. This means that instead of submitting lists of preferences over potential partners to the matchmaker (as it happens in centralized markets) agents engage in active search, make and receive proposals, and eventually get matched (be it to perform a task or a job or to trade goods).[1]

Depending on the particular market, agents may have different levels of understanding of others' preferences over potential partners and, therefore, intentions. Moreover, the cost of conducting partner search itself varies significantly. The amount of consumed time and money ranges from negligible to important and may dictate the premature end of partner search.[2] Also, how committed agents are to their match depends on legal restrictions and social conventions. In some markets, the virtually face-to-face interaction between the two sides of the market, coupled with the fact that markets are small worlds, make an accepted proposal very difficult to renege on; in others, market dimension renders agents anonymous.

How market culture and other market features affect the matching that ultimately prevails in decentralized markets, as well as the behavior that leads to it, is still an open question. Our aim is to give a step forward in this direction by exploring the impact of three features on both the outcome matching and agents' strategies. These are i) the level of information agents hold, ii) the cost of conducting partner search, and iii) the extent to which agreements are binding.

Even though decentralized matching markets constitute a central institution

[1] In fully centralized two-sided matching markets, the matchmaker produces a matching of the two sides of the market using the lists of preferences each agent submits over the other side of the market. Examples of fully centralized markets are the medical residency match and school allocation in the U.S. Other markets are characterized by a decentralized phase preceding the centralized procedure or are not fully centralized, i.e. not all matches are achieved through the matchmaker. Good examples for these are college admissions and the market for junior economists in the U.S.

[2] This has been widely explored in the search and matching literature, for example by Rogerson [15], and Kagel and Roth [8] or Niederle and Roth [13], respectively.

for economic activity, the literature on these markets is still scarce. In fact, even if theory on two-sided matching markets is by now reasonably developed, the applications of such models to decentralized markets are only a few (see, for instance, Haeringer and Wooders [6], Niederle and Yariv [12], Pais [14]). Moreover, empirical analysis is precluded by the lack of a well-defined protocol of market interactions and the lack of information on agents' preferences for most decentralized markets. Laboratory experiments therefore emerge as the preferred approach to this subject. Building a set of controlled experimental markets that differ only in the studied features provides us with the ideal test for their effects and importance.

Among the few experimental papers on decentralized matching markets, Echenique and Yariv [1] is the closest to ours. They describe experiments aimed at testing whether decentralized matching markets, where all agents can make and receive proposals in an essentially unconstrained way, reach stable matchings and, in case more than one stable matching exists, which stable matching is reached.[3] It turns out that stability is a good predictor of market outcomes and that, in markets where a compromise stable matching exists, this is the one that is reached more often.[4] Our paper departs from theirs mainly in that, in their experiments, subjects always hold complete information on everyone's preferences and their interaction takes place in a frictionless world.

The remaining list of experimental studies that look at decentralized matching markets is not only short, but also rather unrelated to our paper. In Haruvy and Ünver [7], a more rigid structure on the functioning of the market is imposed, namely, only one side of the market is allowed to make offers, one per period, and markets are repeated for a certain number of periods. They show that a stable matching, the one that is optimal for the proposing side of the market, is reached in the majority of cases, independently of the level of information subjects hold. Kagel and Roth [8] study the transition from a decentralized market where unrav-

[3]In a stable matching, no pair of agents who are not matched to each other would prefer to be so matched.

[4]The compromise stable matching does not favor any particular side of the market, in a sense that will become clear in the next section.

eling of transactions occurs to a centralized market. Nalbantian and Schotter [11] look at decentralized matching procedures when agents' payoffs constitute private information. Niederle and Roth [13] consider an incomplete information setting in which one side of the market makes offers to the other side over three experimental periods. They study the effects of the offer structure —namely whether offers can or cannot be put on hold— on the information that gets used in the final matching and on the resulting market efficiency. Finally, a couple of experimental papers (Eriksson and Strimling [3], and Molis and Veszteg [10]) approach one-sided matching markets. This literature successfully demonstrates how controlled laboratory experiments can improve our understanding, but its results (probably due to the small number of studies and replications) are far from showing a complete and detailed picture of decentralized matching markets. Moreover, comparisons across studies are difficult because the lack of a canonical mechanism has created numerous different experimental designs.

In our experiments, each side of the market is composed of five subjects who, given (strict cardinal) preferences over the other side, actively search for a matching partner from the other side of the market. We keep this search process essentially unconstrained, i.e. at any time throughout the game subjects are free to make proposals (although only one at a time) and to accept or reject any proposal received.[5] Moreover, partner search took place under different scenarios that differ in the level of information subjects hold on others' preferences —information can be complete or limited to one's own preferences—, in the cost of issuing proposals —either free or with a positive cost—, and in the degree of commitment —when a proposal is accepted, the subjects involved may either stay in the market and continue issuing and accepting proposals or leave the market.[6] Low informa-

[5]Given that the scarce experimental literature on decentralized matching markets does not agree on the design —and given the absence of theoretical models to test—, we implemented this intuitive market with real-time interaction, primarily inspired by the search game designed by Eriksson and Strimling [3].

[6]We also tested markets that differ in complexity, as captured by the number of stable matchings (either two or three), and the number of rounds required for the deferred-acceptance algorithms —protocols that are used by matchmakers in various centralized markets to produce a

tion levels, positive costs of issuing proposals, and the existence of commitment represent departures from the premises of the theory of two-sided matching. The last two are referred to as "frictions" throughout the paper.

Several findings come out of our analysis. First, taking the complete information, no-frictions scenario as benchmark, market activity as revealed by the number of match offers made is higher under low information and lower when offers are costly or commitment is in place (Result 1). The two market frictions not only affect the level of market activity, but also the timing of actions: costly offers mainly delay proposal issuing, while commitment hinders proposal acceptance. Second, subjects tend to propose to the best partner available in almost every occasion, being slightly less ambitious when offers are made at a cost (Result 2). Costly offers, particularly when coupled with complete information, lead to strategizing behavior: aware of the position they themselves hold in the receivers' preferences, subjects tend to propose more to a single partner —in which case they always target the best available— or to a merely better than the *status quo* matched partner, unveiling their fear of rejection (Result 4). On the other hand, when receiving proposals, our analysis suggests that information and frictions have little impact on behavior. Receivers typically choose the best alternative out of any set of proposals, with little reaction to either market structure (Result 3) or *status* and the proposer's personal history (Result 5). They do not strategically reject proposals, but instead reject fairly constantly offers from partners in the lower part of their preference order.

In what the features of the outcome are concerned, even in the absence of frictions, stable matchings are not the norm, but stability —the rationale behind centralizing some matching markets— is a very powerful driving force. Interestingly, stability levels depend on markets' characteristics and there appears to be a connection between the level of market activity and the proportion of stable matchings: low information levels and the absence of frictions, which tend to be associated to a large number of offers, correspond to the highest stability levels

matching— to converge under truth-telling.

(Result 6). On the other hand, convergence to a stable matching is the quickest when commitment is in place. Surprisingly and in spite of harming stability, commitment also appears to boost efficiency. The treatments with commitment correspond to the highest proportions of Pareto efficient final matchings and to the highest average payoff, whereas costly offers tend to decrease efficiency (Result 7).

To sum up, low information by itself does not seem to drive markets away from stability or efficiency. Market activity is used to overcome the lacking information and stability remains a useful predictor of market outcomes. Nevertheless, when low information is combined with costly offers, which seriously hinder the number of offers, stability is severely affected and efficiency decreases. In fact, this friction affects not just the number of offers, but also its pace and even changes slightly the identity of the receivers. Binding commitment is also associated to lower market activity levels and has a slight negative impact on stability, but at the same time acts as a discipline device, speeding up convergence significantly and boosting efficiency.

The rest of the paper is organized as follows. In Section 2 we present the theoretical background of two-sided matching markets. We describe the experimental design in Section 3. Section 4 summarizes the main results of the experiments and some concluding remarks follow in Section 5.

2 Theoretical background

A (two-sided) matching market consists of two disjoint sets of agents. Each agent is assumed to have preferences on the other side of the market and the prospect of being unmatched. The matching problem reduces to a problem of assigning the members of these two sets to one another. In our experiment, matching is one-to-one, so that each agent can be matched to at most one agent of the other side of the market (or stay unmatched).

For our purposes, a matching is stable if there is no pair of agents who are not matched to each other, but would prefer to be so. Stability is an important concept as, in practice, we only expect stable matchings to survive. If a matching is unstable, there is at least one pair of agents that can easily match and circumvent the original matching.

Gale and Shapley [5] have shown that a stable matching exists for every matching market, by means of an algorithm —henceforth the GS algorithm— that we describe in what follows. Starting from a situation in which all agents are unmatched and given a profile of preferences, in the first step of the algorithm, every agent in one side of the market proposes to the best partner on her list of preferences. Every agent that receives proposals holds at most one —the best according to her list— and rejects the others. In the second step, every rejected agent proposes to the second best partner on her list. Those agents that receive proposals hold at most one, the best on each one's list, among those received and the proposal held in the last step, if any.[7] This procedure continues with rejected agents proposing to the best prospective partner to whom they have not proposed yet and terminates when no proposal is rejected. The obtained matching is stable. Moreover, in case more than one stable matching exists, it is the proposing side-optimal stable matching, i.e. the best matching within the set of stable matchings for every agent in the proposing side, and, simultaneously, the worst stable matching for the side of the market that receives proposals. In this case, the set of stable matchings may also comprise each side's optimal stable matching and other stable matchings that represent a compromise between the two sides of the market.[8]

Some matching markets are centralized, so that each agent submits a list of preferences to a central clearinghouse that produces a matching by processing these lists by means of a matching algorithm. In many successful cases, the GS algorithm is used (see Roth [16]). In this paper we aim at exploring markets where

[7]The fact that proposals are held and not immediately accepted from one step of the algorithm to the other explains the fact that this algorithm is sometimes called as the deferred-acceptance algorithm.

[8]In what follows, we will refer to these matchings, when they exist, as "compromise" stable matchings.

matching is decentralized.

3 Experimental design

3.1 Experimental matching markets

The experimental markets consist of five agents on each side. One of the sides is represented by numbers from 1 to 5, and the other side by letters from a to e. Each letter is to be matched to at most one number and each number to at most one letter. We used the three preference profiles shown in table 1 below. These preference profiles differ in the level of conflict (and therefore complexity) as measured by the size of the set of stable matchings and by the number of steps it takes for the GS algorithms to converge to a stable matching.[9]

When real-life decentralized matching markets are considered, they differ and therefore can be characterized by different levels of information (which may or may not be related to market size) and by a variety of more or less informal rules that govern participants' behavior. For this reason, our experimental treatments have been constructed along two characteristics: the level of information agents hold about others' preferences, and the (in)existence of what we call "frictions," i.e. a cost for issuing proposals and the obligation to commit to a match. We briefly describe these features in what follows.

In the low-information environments participants' preference profiles are private information. Participants know their own preferences as reflected in their payoff tables and the only information that we give them about the others' is that "they are similar,"[10] whereas in the high-information environments participants know the entire preference profile.

[9]Markets 1 and 3 have three stable matchings, whereas market 2 has only two. It takes 3, 6, and 2 steps for the GS algorithm with letters proposing to converge and 3, 5, and 3 steps with numbers proposing to converge in markets 1, 2, and 3, respectively.

[10]We do not specify any probability distribution or upper and lower limits for the others' valuations in the low information treatment.

Table 1: Preference profiles

letter	. ≻ . ≻ . ≻ . ≻ .	number	. ≻ . ≻ . ≻ . ≻ .	stable matchings	
			market 1		
a	$1 \succ 3 \succ 5 \succ 2 \succ 4$	1	a ≻ c ≻ e ≻ b ≻ d	number-optimal	$(1a, 2b, 3d, 4e, 5c)$
b	$1 \succ 2 \succ 4 \succ 3 \succ 5$	2	a ≻ b ≻ d ≻ c ≻ e	letter-optimal	$(1a, 2b, 3c, 4d, 5e)$
c	$2 \succ 1 \succ 3 \succ 4 \succ 5$	3	b ≻ a ≻ d ≻ e ≻ c	compromise	$(1a, 2b, 3e, 4c, 5d)$
d	$2 \succ 1 \succ 4 \succ 5 \succ 3$	4	b ≻ a ≻ e ≻ c ≻ d		
e	$1 \succ 2 \succ 5 \succ 3 \succ 4$	5	a ≻ b ≻ c ≻ d ≻ e		
			market 2		
a	$2 \succ 3 \succ 4 \succ 5 \succ 1$	1	c ≻ d ≻ b ≻ a ≻ e	number-optimal	$(1e, 2a, 3d, 4c, 5b)$
b	$3 \succ 5 \succ 2 \succ 1 \succ 4$	2	a ≻ c ≻ d ≻ b ≻ e	letter-optimal	$(1e, 2a, 3b, 4c, 5d)$
c	$2 \succ 3 \succ 4 \succ 5 \succ 1$	3	a ≻ d ≻ b ≻ c ≻ e		
d	$2 \succ 5 \succ 3 \succ 1 \succ 4$	4	c ≻ d ≻ e ≻ a ≻ b		
e	$3 \succ 4 \succ 2 \succ 5 \succ 1$	5	c ≻ a ≻ b ≻ d ≻ e		
			market 3		
a	$1 \succ 3 \succ 5 \succ 2 \succ 4$	1	a ≻ b ≻ d ≻ e ≻ c	letter-optimal	$(1a, 2b, 3d, 4e, 5c)$
b	$1 \succ 2 \succ 4 \succ 3 \succ 5$	2	c ≻ a ≻ b ≻ d ≻ e	number-optimal	$(1a, 2b, 3c, 4d, 5e)$
c	$3 \succ 4 \succ 5 \succ 1 \succ 2$	3	d ≻ e ≻ c ≻ b ≻ a	compromise	$(1a, 2b, 3e, 4c, 5d)$
d	$4 \succ 5 \succ 3 \succ 2 \succ 1$	4	e ≻ c ≻ d ≻ a ≻ b		
e	$5 \succ 3 \succ 4 \succ 1 \succ 2$	5	c ≻ d ≻ e ≻ b ≻ a		

In some environments issuing offers is free of cost, whereas in others partner search is costly. In this case, offers have a fixed cost that subjects pay from their initially allocated budget, large enough to avoid bankruptcies.[11]

Finally, no-commitment environments allow matched couples to stay in the market and send and receive offers during the whole market round privately.[12] In case an already-matched participant's offer is accepted or an already-matched participant accepts a new offer, the old existing partnership is dissolved and the new one formed (leaving the abandoned partner alone). In contrast, acceptance is binding in commitment treatments, so that matched couples leave the market immediately.

[11]The per-offer cost was 4 Experimental Monetary Units (EMU) for an initial budget of 16 EMU. The part of the budget that had not been spent on sending offers was added to the subjects' final payoff in each round. A conveniently adjusted conversion rule from EMU to euro made sure that subjects earned the same amount of money on average in all our treatments.

[12]Note that in every environment agents on both sides of the market can issue proposals.

3.2 Experimental procedures

Our experiment was conducted at LINEEX at the University of Valencia, with 180 students recruited online and by using the z-Tree software (Fischbacher [4]). At the beginning of each session, printed instructions were given to subjects and were read aloud to the entire room. These instructions explained all the rules determining the resulting payoff for each participant. They were written in Spanish and presented sample screens to illustrate how the program worked. The English translation of the instructions along with a sample of the screen that a participant would look at can be found in Appendix B.

At the beginning of each market round the computer randomly assigned subjects to groups of ten and, within each group, sorted them into two sets, numbers and letters. We used anonymous stranger matching, i.e. participants were not informed about who the other members of their group were, and they were informed that both groups and sets were changing randomly throughout the session. Subjects were not allowed to communicate with each other (other than sending and deciding over offers on the screen).

At any time throughout the games a subject could issue proposals to any participant on the other side of the market, i.e. in the other set of the same group, or react to the proposals she receives. However, a participant could only make one offer at a time, i.e. could not send a new offer until the previous one had been either accepted, rejected by the other participant, or withdrawn by herself.

The status of an offer could therefore be pending (sent, but not accepted or rejected by its recipient), accepted, rejected, withdrawn (by the sender), or abandoned (if it has been accepted, but at least one party has accepted a different offer later). Participants could also send an offer to themselves and accept it freely in order to become single again at any moment in time (provided they did not have any pending offer among the offers they had sent).

In order to keep the amount of real-time information on screen manageable (and because it sticks better to reality in most matching markets), a participant only received information on the status of the offer she made and received, and on the current matching in her market.

As mentioned above, experimental conditions varied across two dimensions, information and existence of frictions, resulting in a 2×3 design.[13] Table 2 below contains a summary of our treatments. We conducted one session for each treatment. Subjects participated in only one session, in which they played each of the three matching markets described above (each one characterized by a different preference profile) five times in a row, each time in randomly changing role (and ID). Each session therefore consisted of fifteen rounds of play, plus one practice round and lasted around 90 minutes.

Table 2: Treatment summary

feature	TRTs 1 - 6					
group size	5 + 5					
rounds	(1) + 3×5					
preference profile	two or three stable matchings					
market activity	two sides offer					
timing	real-time action					
# of offers	one at a time					
feature	TRT 1	TRT 2	TRT 3	TRT 4	TRT 5	TRT 6
offer	free	costly	free	free	costly	free
commitment	no	no	yes	no	no	yes
information	high	high	high	low	low	low
# of subjects	30	30	30	30	30	30

At the end of the session, subjects were paid individually and confidentially. Subjects' preferences were induced by the monetary payoff that they earned depending on who their partner was at the end of each round.[14] These payoffs were similar across subjects. Every subject got 50 Experimental Monetary Units (EMU) for the top choice, 40 for the second choice, 30 for the third, 20 for the fourth, 10 for the fifth, and 0 when she ended up alone. The final payoff of the

[13]Treatments with both costly offers and commitment were not tested in the laboratory.

[14]In the treatments where rematches are allowed, this rule implies that the intermediate matches are worth zero as if they belonged to an "interview phase."In other words, in a world without commitment, the only thing that matters is what you get in the end.

session was computed as the accumulated payoff over the fifteen paying rounds and amounted to 15€ for the average subject, including a show-up fee.

4 Experimental results

4.1 Profile and experience

Although the implemented markets are fairly similar in structure, the different preference profiles might have had some minor, yet significant, effect on behavior and outcomes. One could argue that in terms of conflict (proxied by the number of rounds it would take GS algorithms to converge to a stable matching), profile 2 yields the most difficult game, while profile 3 leads to the easiest and profile 1 to an intermediate benchmark case. On the other hand, profiles also differ in the number of stable matchings: profile 2 yields two stable matchings, whereas both profiles 1 and 3 yield three stable matchings. Finally, if subjects' experience is of any importance, it should affect the game with profile 2 slightly (played second) and with profile 3 significantly (played last).

Nevertheless, even if it is true that market activity (number of offers and deals) decreases with experience, rationality (except for some significant drops in treatments 2 and 4 in the difficult market 2) and other measures expressed in percentage terms (acceptance, rejection, and withdrawal rates) seem to be stable across games. Additionally, we could not discover any clear pattern in the evolution of efficiency and stability over games induced by different profiles and time either.

In light of these observations and for the sake of a more focused analysis on market frictions, in what follows, we present the analysis of the pooled database (the three profiles together) across experimental treatment (which also defined our sessions).

4.2 General observations

Table 3 contains statistical results on market activity at subject level. Depending on the treatment, the average subject proposed between 4.9 and 15.2 times and accepted between 2.5 and 4.6 offers. The per-game average number of rejections and withdrawals varied between 0.6 and 5 and 0.5 and 5, respectively, and the number of abandoned deals per subject in the no-commitment treatments is low, ranging from 0.6 to 2.1.

Table 3: Subject-level activity

	TRT1	TRT2	TRT3	TRT4	TRT5	TRT6
# offers	10.8	4.9	7.3	15.2	6.3	8.0
# withdrawals	3.8	0.9	0.5	5.0	1.4	0.5
(% of all offers)	36%	18%	7%	33%	22%	6%
# acceptances	3.5	2.8	2.5	4.6	3.2	2.5
(% of non-withdrawn offers)	50%	71%	34%	45%	66%	31%
# rejections	1.6	0.6	0.5+3.8	3.6	0.8	0.6+4.4
(% of non-withdrawn offers)	23%	15%	6%+53%	35%	17%	8%+55%
# ever-pending offers	1.8	0.6	0.0	2.0	0.9	0.0
(% of non-withdrawn offers)	26%	14%	0%	19%	18%	0%
# abandoned deals	1.1	0.6	-	2.1	0.9	-

NOTE. These numbers are averages of subjects' decisions in the 5 rounds that each market was played. In TRT3 and TRT6, the number of rejections includes the number of offers that were actually rejected per subject in each game —0.5 and 0.6, respectively— and the number of offers that were automatically cancelled, when, for instance, its issuer accepted another proposal and therefore left the market —3.8 and 4.4.

These numbers show that market activity is severely affected by the level of information and frictions. On the other hand, independently of the treatment, almost every decision is "rational" in the sense that it tries to improve upon the *status quo*.[15] The proportion of "rational" proposals (made to potential partners that are better than the *status quo*), of "rational" acceptances (that improve upon the receivers' *status quo*), and the proportion of "rational" deals (where both sides

[15]Clearly, an "irrational" decision in our setting still may correspond, in fact, to some sort of optimal strategizing that we are not aware of, so that the term "rationality" should not be taken literally.

improve, thus corresponding to a match of a blocking pair) are contained in table 4.

Table 4: Rationality

		TRT1	TRT2	TRT3	TRT4	TRT5	TRT6
# offers		971	445	654	1365	570	719
	# rational offers	956	444	654	1354	559	719
	% rational offers	98%	100%	100%	99%	98%	100%
# acceptances		315	256	225	413	290	224
	# rational acceptances	305	252	225	399	282	224
	% rational acceptances	97%	98%	100%	97%	97%	100%
# deals		315	256	225	413	290	224
	# rational deals	301	252	225	392	275	224
	% rational deals	96%	98%	100%	95%	95%	100%

The influence of information and frictions on market activity and rationality is stated in the following result.

Result 1 (Market activity and rationality) Low levels of information correspond to high levels of market activity, whereas costly offers and commitment reduce market activity. Rationality is very high and does not appear to be affected by the level of information or any of the frictions.

First, in the absence of information on the others' preferences the number of offers and corresponding reactions is higher, particularly in the absence of frictions. One possible reason for this is that offers can be used as a means to extract information: Subjects may issue proposals to become aware of the position they themselves occupy in their potential partners' lists. In many cases, such proposals are not acceptable by a receiver who is acting rationally. Costly offers and, to a greater extent, commitment, increase the cost of such behavior.

This explains the higher number of offers and rejection rates under low information, this difference being particularly relevant in the absence of frictions.[16] Interestingly, the acceptance rates —the proportions of non-withdrawn offers that

[16]Comparing the two information scenarios, the number of offers under low information is 41%,

are accepted— are roughly 10% lower under low information than under full information independently of the existence of frictions.[17]

Second, both costly offers and commitment appear to discipline behavior in the following sense. The levels of market activity are significantly lower: The number of offers and corresponding reactions fall significantly, particularly when offers become costly.[18] Also, offers appear to be better thought through by the subjects as the withdrawal rates fall significantly in both cases, particularly when commitment is introduced.[19]

Moreover, when offers are costly, a bigger proportion of the offers made are actually acceptable —and end up being accepted—, whereas the rejection rates fall.[20] The number of abandoned deals is also much lower when offers are costly. This appears to confirm the less erractic behaviour when issuing proposals is costly.

Introducing commitment has a different effect on acceptance and rejection rates: whereas the former falls slightly, the latter increases significantly.[21] The reason behind this lies in the fact that, with commitment, accepting an offer implies abandoning the market. Besides being a decision to be well thought through, by construction, each subject can accept at most one proposal.[22] Many proposals

28%, and 10% higher than under full information in the absence of frictions, when issuing proposals is costly, and when there is commitment, respectively. The corresponding rates of change for the rejection rate are 50%, 7%, and 5%.

[17]In the low information scenario, the acceptance rate is 10%, 7%, and 10% lower than in the full information scenario in the absence of frictions, when proposing is costly, and when there is commitment, respectively.

[18]For instance, the number of offers falls 54% and 58% under high and low levels of information, respectively, when proposals are costly. The corresponding rates of change are 33% and 47%, when commitment is enforced.

[19]Withdrawal rates decrease 48% and 32% under high and low levels of information, respectively, when proposals are costly. The corresponding rate of change is 81%, for both information levels, when commitment is enforced.

[20]When offers become costly, the acceptance rate increases 40% and 45% and the rejection rate falls 34% and 53%, under the full and low information scenarios, respectively.

[21]With commitment, the acceptance rate decreases 27% in both information scenarios and the rejection rate increases 169% and 89%, under the full and low information scenarios, respectively.

[22]This explains why the average number of per–game acceptances with commitment is 2.5 under both information scenarios: Since almost all subjects pair up in every round, each subject

therefore end without ever being responded to and are cancelled once the proposer leaves the market.

The levels of rationality are everywhere extremely high and do not appear to depend significantly on the treatment we consider. Note, however, that the reason why commitment (treatments 3 and 6) always guarantees full rationality lies in the definition of rationality we adopted: Since only unmatched agents are in the market and all potential partners are acceptable in every game, each proposal and each acceptance is, by definition, rational.

Figure 1 in Appendix A sheds some more light on the impact of frictions on market activity. It shows that it is not just the number of offers that varies across treatments, but the timing of decisions is also clearly different: as the pressure to make a match is the highest when there is commitment, the number of offers is very high in the first rounds, falling sharply afterwards. Costly offers, on the other hand, make subjects think harder, so that the number of proposals is not just lower in total, but decreases smoothly as the game proceeds. In the absence of frictions proposers behave like an intermediate case and information appears mainly to have a scaling effect, the number of offers being always slightly higher under low information as the game proceeds.

The evolution of acceptances over time is in figure 2. Again, the observed pattern depends on the treatment, as it is certainly the case that the evolution of acceptances over time is conditioned by the evolution of offers. Two points are perhaps worth noticing. First, unsurprisingly, acceptance is much more cautious when commitment exists: despite the huge number of offers in the first rounds, acceptance is delayed when compared with the no-frictions treatment. Second, when proposals are costly, despite the decreasing number of offers as time passes, many are accepted close to the end of the game.

To sum up, both costly offers and commitment hinder market activity, but, quite unsurprisingly, whereas the former mainly constrain the number and pace of proposals, the latter acts mainly on acceptance. The lack of information boosts

accepts an average of 0.5 proposals in each round.

market activity throughout the games.

4.3 Individual behavior and frictions

In this section we go deeper into the analysis of subjects' behavior. The following table and results provide some numbers and a brief description of the most interesting features, respectively.

Table 5: Individual behavior

		TRT1	TRT2	TRT3	TRT4	TRT5	TRT6
offer	first to	45.9	41.7	47.0	47.4	45.0	47.4
	second to	38.0	31.8	34.3	38.8	35.2	36.4
	third to	36.3	32.7	25.2	39.2	31.6	25.6
	% when matched	24.7%	6.3%	0.0%	39.4%	14.7%	0.0%
	% to matched	30.1%	13.9%	0.0%	43.5%	18.4%	0.0%
	average repeated offers	0.47	0.02	0.05	1.02	0.06	0.04
acceptance	% best from	94%	97%	97%	91.3%	95.9%	99%
	% when matched	16.6%	12.3%	0.0%	20.9%	11.0%	0.0%
	% with 2+ offers	24.8%	16.6%	0.0%	29.9%	17.9%	0.0%
	pending offers	1.3	1.2	1.0	1.4	1.2	1.0

NOTE. The reported numbers are per–subject averages. For instance, first to, second to, and third to correspond to the average of each subject's average first, second, and third offers across games, respectively.

Result 2 (Proposers' behavior) In the absence of frictions, subjects propose in order of preference and tend to repeat offers to their best partners when rejected. When offers are costly, subjects display some skipping behavior and start with slightly more humble first offers. With commitment, subjects propose in order of preference.

When commitment exists (treatments 3 and 6), the strategy chosen by the average proposer can easily be explained. There, acceptance of a subject's proposal means that she will exit the market, so that ambitious proposals in the first rounds were to be expected. As such, on average subjects propose to their preferred partner first, to their second best partner second, and to their third best partner third.

In fact, referring to figure 1 once more, the proportion of proposals made to the best partner available in the market is very high throughout the whole game. The average payoff of all proposers in each moment in time, also in figure 1, confirms that with commitment subjects start by proposing to their best partners and, as those subjects that match in the begining of the game ususally get their most preferred partners, they obtain high payoffs. As the games proceed, those that are left propose to potential partners who are still in the market, but that on average they value less, so that the payoff of the average proposer falls sharply. Close to the end of the games, the remaining subjects pair up and payoffs rise again.

In treatment 1 there are no costs to issuing offers nor commitment and therefore nothing is foregone when proposing to the best partner, even if this partner ranks her low in her preference list. So, subjects start proposing in order of preference and, even if a reasonably good match is obtained, they keep on proposing to their best partners, so that the payoff of the average proposal decreases only slightly throughout the games.[23] The same kind of behavior is observed in treatment 4, as starting to propose in order of preference is further enhanced by the lack of information.

It is also interesting to observe how costly offers affect proposers' behavior: besides reducing the number and pace of offers (as seen above), the utilities associated to the first receivers are on average slightly lower. And prudence, shown by higher proportions of proposals to partners that are better than the *status quo*, but not the best available, is present throughout the games.

In what receivers' behavior is concerned, a feature is common to all treatments: subjects tend to accept the best available offer in the huge majority of cases. The proportions of acceptance of the best available offer are slightly lower in the two treatments that do not have frictions (treatments 1 and 4), where such form of behavior —which may be a reflection of strategizing— comes at a lower cost.[24]

[23]To reinforce this statement, note that the average number of repeated offers is much higher in the absence of frictions.

[24]Accepting an offer other than the best pending offer, as well as acting irrationaly or not propos-

Result 3 (Receivers' behavior) Subjects tend to accept the best available offer.

It is also interesting to note that, when no commitment is enforced, subjects typically do not respect established partnerships. Subjects propose when matched and to matched agents; however, the frequency of such proposals is lower with costly offers and complete information. Costly offers increase the cost of such behavior. And, when holding information, subjects compare the position they themselves are held in their target partner's preferences with their current partner and this may prevent them —particularly when they are already matched— from proposing to a married partner, in case he is assigned to a better ranked match. Acceptance of proposals is also often made at the expense of breaking a match.

Nevertheless, decisions that lead to match breaking or involve more than one proposal at a time represent the minority of all decisions and the typical decision situation is actually close to the one-offer, one-decision situation.

4.3.1 Naïve behavior

We now take a further step in explaining subjects' behavior by means of naïve decisions, defined as follows. Each naïve proposing or accepting decision class combines two dimensions: The status (single or any) of the proposer or the receiver, respectively, and the history of the proposer-receiver pair (not matched or rejected before, not matched before, or any). We thus obtain six decision classes for each side of the market as shown in the next table.

Among the subjects that make these decisions, we then check within each proposing and acceptance decision class what is the proportion of offers to and acceptances from, respectively, a partner that is the best potential partner available or merely better than the *status quo*. Failing to belong to one of these categories means that the decision was either irrational or falls out of the decision class we are considering.[25] The numbers are contained in table 7 and the main conclusions

ing in order of preference, may be reflections of strategizing behavior. Costly offers and, to a greater extent, commitment, increase the cost of strategizing, which explains the above fact.

[25]For instance, referring to table 7 and considering the strategy S3 in TRT1, 56% of the offers

Table 6: Feasible sets for naïve strategies

strategy	status (from/to)	history (from/to)
A/S 1	singles only	not matched or rejected before
A/S 2	singles only	not matched before
A/S 3	singles only	-
A/S 4	-	not matched or rejected before
A/S 5	-	not matched before
A/S 6	-	-

NOTE. An "A" strategy is an acceptance strategy and an "S" strategy is a proposing strategy.

follow.

Result 4 (Proposers' naïve behavior and the impact of frictions)

1. When personal history and the receiver's status are ignored, almost all proposals are made to make the sender better off. They are evenly split between offers to the best available partner and offers to "just" improve upon the *status quo*.

2. The effect of history is negligible.

3. In treatments with costly offers the proportions of rational proposals made to singles are higher than in treatments without frictions. Under complete information this effect is mainly due to a higher proportion of offers made to a partner better than the *status quo*, whereas under low information it is the proportion of proposals made to the best available partner that contributes to the difference.

4. When holding complete information, the proportion of rational proposals made to singles is higher than when holding low information. When offers are costly, this is due to a higher proportion of proposals made to potential

made were to the best available single, 13% to a single other than the best that is still better than the *status quo*, and 31% to either a worse single partner or to a matched subject.

single partners that are better than the *status quo*. In the absence of frictions, the proposals made to the best available single and to a better than the *status quo* single increase (notably the former).

It comes as no surprise that in treatments with commitment the huge majority of all offers throughout the games are made to the best available partner. Still, table 7 unveils a factor that may explain this behavior: in every treatment subjects propose mainly to the best available single,[26] but to a better than the *status quo* matched partner.

Moreover, full information increases the proportion of rational proposals made to singles. Table 5 showed that the proportion of proposals to singles is higher with full information; we now know that this is due to a higher tendency to propose to a better than the *status quo* single, notably when offers are costly. Costly offers inhibit proposals to the best available partner when information is complete.

Furthermore, there is no evidence of punishment since history hardly affects proposing behaviour. It therefore appears that the only reason why subjects do not propose to a former partner or to someone who rejected them previously is because they fear a rejection, event that is more likely when that subject is matched.

Fear of rejection therefore seems to explain why subjects do not always propose to the best available partner, particularly when this subject is matched. Even though subjects do not have any problems with breaking a relationship (see numbers in table 5) and punishment does not seem to have a role, proposing to a matched subject comes at a higher risk. This risk is known and often avoided when there is full information. Proposals to matched subjects are also lower with costly offers, which simply act as expected by raising the opportunity cost of such behavior.

A last note on receivers' behavior. As seen above, in general, receivers accept the best available offer. The only point perhaps worth noticing is that costly offers increase the proportion of rational acceptances, particularly of proposals from

[26] And, in treatments with commitment, all available partners are single.

single subjects or from subjects that were previous partners.[27] This may merely reflect the fact that, when offers are costly, a greater proportion of proposers are single (see table 5) or were previous partners. The following result concludes this section on naïve behavior.

Result 5 (Receivers' naïve behavior and the impact of frictions) Receivers tend to accept the best proposal available, they do so practically independently of the treatment, of the *status,* and of the personal history of the proposer.

4.4 Aggregate outcomes and frictions

The level of stability of the final matching ranges from 31% to 82%, reaching its lowest value under low information when offers are costly.[28] One possible explanation for this extremely low value is that costly proposals, by hindering market activity, do not allow enough information to be transmitted, making the combination of low information with costly proposals particularly harmful for stability. On the other hand, under each information level, the highest levels of stability of the final matching are reached in the no-frictions treatments, suggesting that market frictions may, in fact, deter a decentralized matching market from reaching stability, the driving force behind the design of centralized matching markets. Table 8 contains the relevant numbers and we summarize the main points in the result that follows.

Result 6 (Stability and the impact of frictions)

1. Treatments with costly offers and forced commitment correspond to lower proportions of stable final matchings than treatments without frictions.

2. Low information levels correspond to a higher proportion of stable final matchings, except when offers are costly.

[27] Commitment leads to 100% rationality as all acceptances are, by definition, rational.

[28] The numbers reported in Echenique and Yariv [1] were 89% and 47% in frictionless markets under complete information with two and three stable matchings, respectively.

3. Under each information level, convergence to a stable matching is the quickest in the commitment treatment, followed by the no-frictions treatment, and the costly offers treatment.

Another perspective on stability is given by the average number of blocking pairs to the final matching. It achieves the highest values when offers are costly and values close to the no-frictions treatments when commitment is in place.[29] Therefore, there is an apparent connection between the level of market activity, which is particularly affected by costly offers, and the levels of stability. In fact, to more active markets, as proxied by higher numbers of offers —either when no frictions exist or when information is low— correspond higher levels of stability.

A last couple of remarks on stability and on the predictive power of the GS algorithms. In markets 1 and 3, the compromise stable matching is the most frequent matching among the stable matchings that are obtained. This was somehow expected given the symmetric role of the two sides of the market and the frequencies reported in Echenique and Yariv [1].[30] For comparison purposes, we also computed the number of times the outputs of the Boston algorithms are reached, but it turns out that these numbers are low.[31]

In what efficiency is concerned, its levels are quite high in every treatment.[32] Moreover, frictions appear to influence efficiency levels as stated in the following

[29]In treatments with costly offers this happens as a result of two effects: The proportion of stable matchings is lower than when no frictions exist and the average number of blocking pairs of each unstable matching is much higher —3.3 and 2 in TRT2 and TRT5, respectively, against 2.6 and 1.7 in TRT1 and TRT4. With commitment, the proportion of stable matchings is lower than without frictions, but the average number of blocking pairs of each unsatble matching is also lower —1.3 and 1.4 in TRT3 and TRT6, respectively.

[30]We remind the reader that in this experiment both sides of the market can make proposals, whereas the GS algorithm leads to the optimal stable matching for the proposing side of the market.

[31]The Boston algorithm was used in Boston —and in other cities— to assign students to schools. In the Boston algorithm the side of the market that receives proposals cannot hold, but only accept or reject proposals, so that the outcome matching may fail to be stable with respect to submitted preferences. Otherwise, its description is similar to the one provided for the GS algorithms.

[32]The high proportions of efficient outcomes are partly due to the number of Pareto efficient matchings that exist in each game: market 1 has 109, market 2 has 82, and market 3 has 32 Pareto efficient matchings out of a total of 120 possible complete matchings and 1546 possibly incomplete matchings.

result.

Result 7 (Efficiency and the impact of frictions)

1. Treatments with commitment correspond to the highest efficiency levels, followed by treatments without frictions, whereas costly offers present the lowest efficiency levels.
2. The proportion of efficient final matchings is in general slightly higher under low information.

Surprisingly, in spite of reducing stability, commitment appears to enhance efficiency, whereas costly offers have a negative effect on both counts. Low information levels are associated with slightly higher levels of efficiency.

5 Conclusion

Most decentralized matching markets have freely evolved to exhibit a variety of features, while keeping virgin to market designers' intervention and unnoticed to the eyes of theorists. Still, the pervasiveness and variety of decentralized matching markets provide an irresistible urge to their careful study and this paper is one of the first steps in this direction.

We reported results from experiments on a series of markets differing in the level of information agents hold on others' preferences, the cost of conducting partner search, and the bindingness of commitment. It appears that agents in these markets engage in strategic thinking, particularly when taking the lead and issuing proposals, while essentially reacting to received proposals in a straightforward way. Strategizing is evident as our experiments show that proposing behavior depends on markets' features, be it in the number and pace of offers made or the identity of the receivers.

In what outcomes are concerned, even though stability remains a fairly good predictor of market outcomes in every treatment, since behavior is determinant in shaping market outcomes, the obtained matching is responsive to the environment. Namely, low information on others' preferences boosts both stability and efficiency of the final matching via an increased market activity. Costly offers have a negative impact on both, but surprisingly commitment enhances efficiency, while reducing stability (but speeding up the convergence process).

This leads us to two final remarks on the grounds of mechanism design. First, we noted that even in the presence of frictions the proportion of stable final matchings remains high. Introducing binding commitment, which brings the functioning of a market closer to the description of the Boston algorithm, could be expected to increase the proportion of Boston outcomes, but it does not. It appears that agents adapt behavior to guarantee stability, which remains a powerful driving force. This can be taken as an additional incentive to implement centralized clearinghouses that produce stable matchings.[33]

The second remark concerns the importance of frictions. If the lack of information on others' preferences by itself does not have to be a concern as our results suggest that it be easily overcome, policy makers and matching theorists should be ware of frictions, which appear to affect desirable properties of the outcome. For instance, the combination of low information levels and costly search is particularly detrimental to stability, so that the benefits of introducing a centralized clearinghouse that implements a stable matching in markets that exhibit these features are potentially high.

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[33] In fact, as Echenique and Yariv [1] put it, any decentralized matching process that might precede the centralized phase would only push the outcome towards stability.

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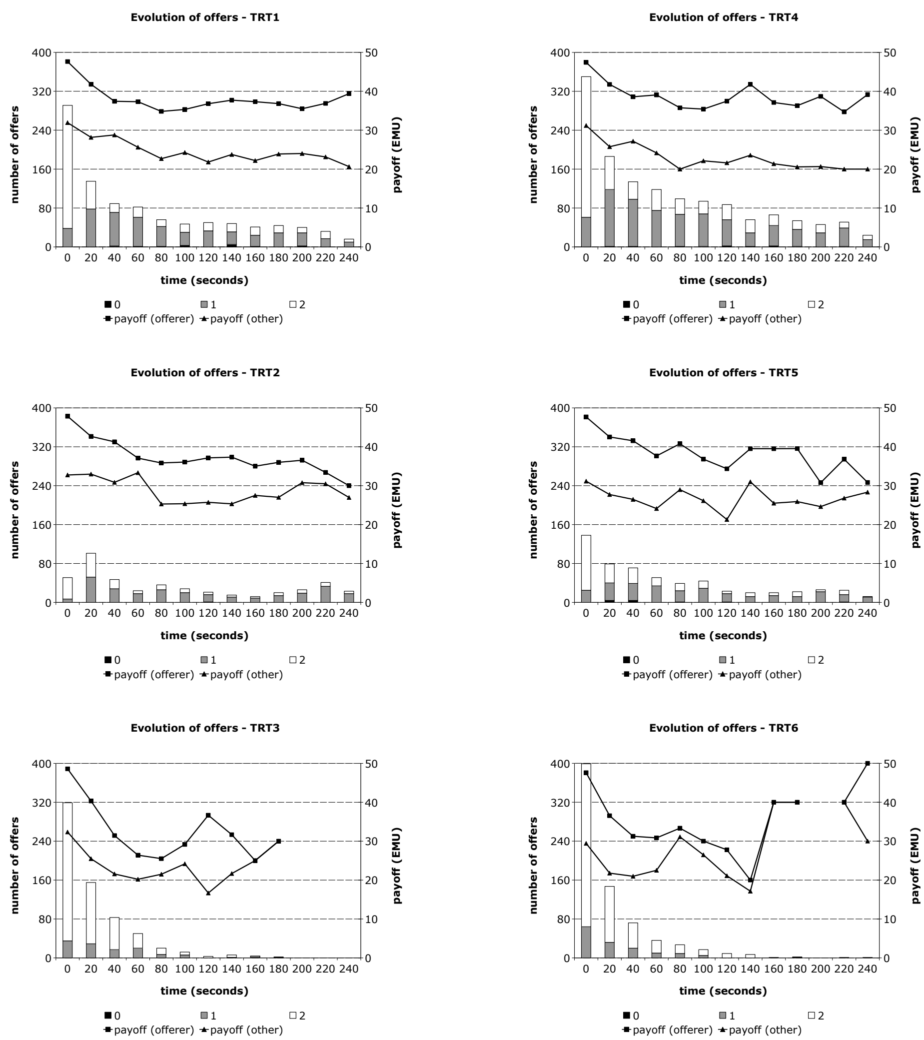
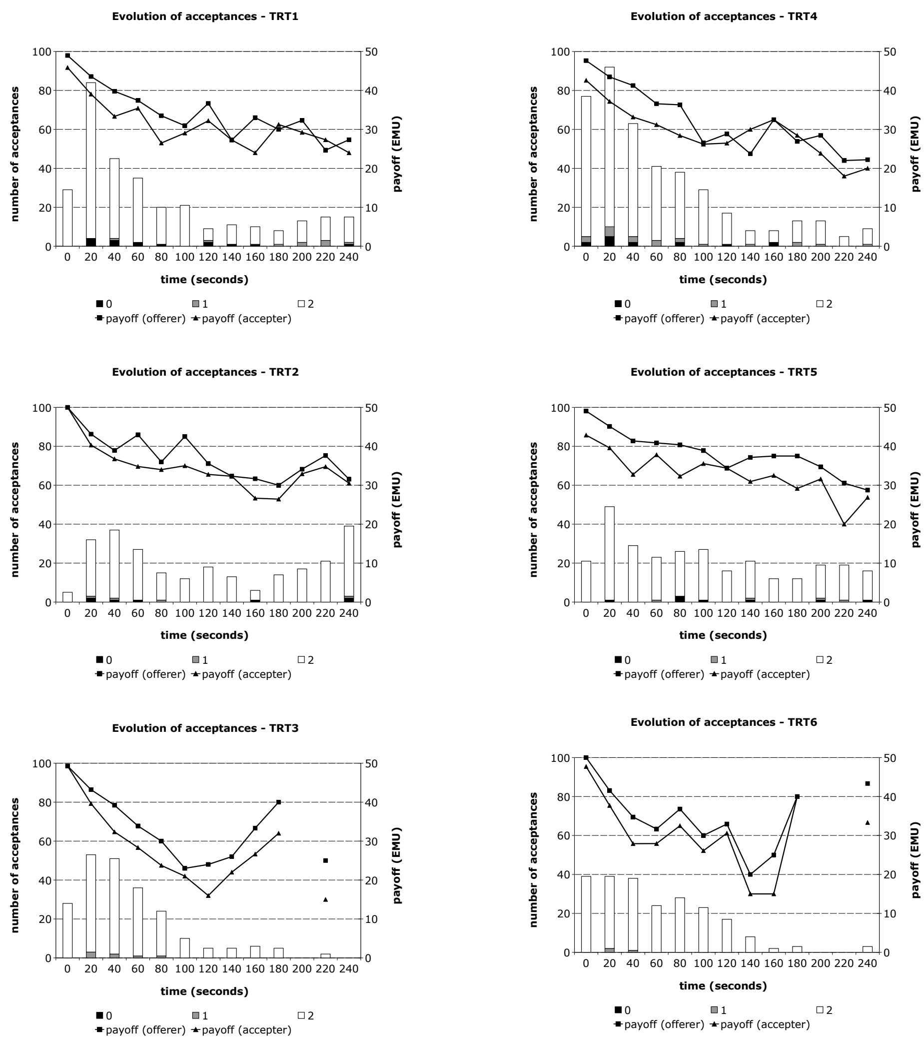
A Additional figures

Figure 1: Evolution of offers over time



NOTE. 0 corresponds to irrational offers, 1 corresponds to offers made to a partner that is better than the status quo, and 2 corresponds to offers made to the best available partner. The offerer's payoff is computed as the average of the proposals made at each moment in time. The other's payoff is the average of the payoffs of all subjects receiving proposals at each moment in time in case they would accept them.

Figure 2: Evolution of acceptances over time



NOTE. 0 corresponds to irrational acceptances, 1 corresponds to acceptances of offers from a partner that is better than the status quo (but not the best available offer), and 2 corresponds to acceptances of the best offer received. The offerer's payoff is computed as the average of the payoffs of all subjects whose proposals are accepted at each moment in time. The accepter's payoff is the average of the payoffs of all subjects accepting proposals at each moment in time.

B Instructions for the experiment - TRT 1

The objective of this experiment is to study how people make decisions in certain situations.[34] Should you have a question, you can pose it at any moment by first

[34]These instructions correspond to treatment 1 and constitute the benchmark. All the other instructions, both in Spanish and English, along with the zTree programs are available upon request

raising your hand. From this moment on, you are not allowed to talk to the other participants.

The instructions are simple and if you follow them carefully, you can earn some cash that you will receive at the end of the experiment. Your monetary payoff will partially depend on your decisions and also on the decisions made by the others in the group. At the end of the session, payments will be made confidentially, so no one will receive information on the other participants' earnings.

Instructions

This session consists of one practice round and 15 rounds that will determine your final payoff. At the start, the computer will randomly assign the participants to groups of 10 people. No one will know the identity of the other members' in the group. Moreover, the assignment will change in each round, therefore the composition of your group is very likely to change from round to round.

Each group will be divided in two subgroups of 5 people. The members of one subgroup will be identified by capital letters from A to E, while the members of the other will be identified by numbers from 1 to 5.

In each round, you will randomly be assigned an ID: a capital letter from A to E, or a number from 1 to 5. Your task is to find a partner in the other subgroup. If you wish, you can also remain alone. Only partnerships formed by one capital letter and one number are allowed.

In order to describe how partnerships are formed in this experiment, we have attached a figure that show a screen similar to the ones you will be seeing during the experiment. Let us suppose that in this round you have been assigned the capital A as your ID. The other participants look at similar screens.

Your ID is shown in the upper central part of the screen.

from the authors.

On the upper part of the screen to the left you see the payoff table that shows the amount of money that you can earn at the end of the round depending on who your partner is (at the end of the round). These amounts are expressed in Experimental Monetary Units (EMU).

On the upper part of the screen to the right you see the status (the partner) of all the particiapants in your group. At the beginning of each round, everybody is alone.

On the upper central part of the screen, below your ID, you will find your current partner's ID and also the payoff that you can earn if that person remains your partner until the end of the round. In this example, you are alone. and if the round ends like this, you would earn 0 EMU.

It is important that the payoff table displays the amount of money that you will be earning (at the end of the round) depending on with whom you are forming a partnership. In this example, you would earn 50 EMU by forming a partnership with Participant 1, 20 EMU by forming a partnership with Participant 2, etc. The screen only displays your possible earnings, but on a separate paper sheet you will also receive information about the possible earnings of the other participants. During the first 15 rounds you should be considering the data in table 1, during the next 5 rounds you should be considering the data in table 2, and during the last 5 rounds the data in table 3.

In order to send an offer to form a partnership, write an ID in the purple cell that appears on the upper central part of the screen and clic on the "send offer" button. If your ID is a number, you are only allowed to write capital letters and your own ID number (in case you want to be alone). If your ID is a letter, you are only allowed to write numbers and your own ID letter (in case you want to be alone).

The lower part of the screen shows the list of offers that you have sent and the list of the offers that you have received. To the left is the list of received offers. The table displays who sent the offer and also the status of the offer ("pending" for all new offers). To accept or to reject an offer, you have to select the row of the offer and then clic on one of the buttons: “accept offer” or “reject offer”. The status of the offer will change accordingly immediately.

If you accept an offer or your offer is accepted, the ID of your partner and your expected payoff are updated immediately. To the right you find the list of offers that you sent. If you regret having sent an offer, you can withdraw it at any moment (if it is still pending).

It is important that you are not allowed to send several offers at the same time. This means that you are only allowed to send a new offer if the previously sent has already been accepted, rejected (by its recipient) or withdrawn (by you).

There are three ways of staying alone in this experiment.

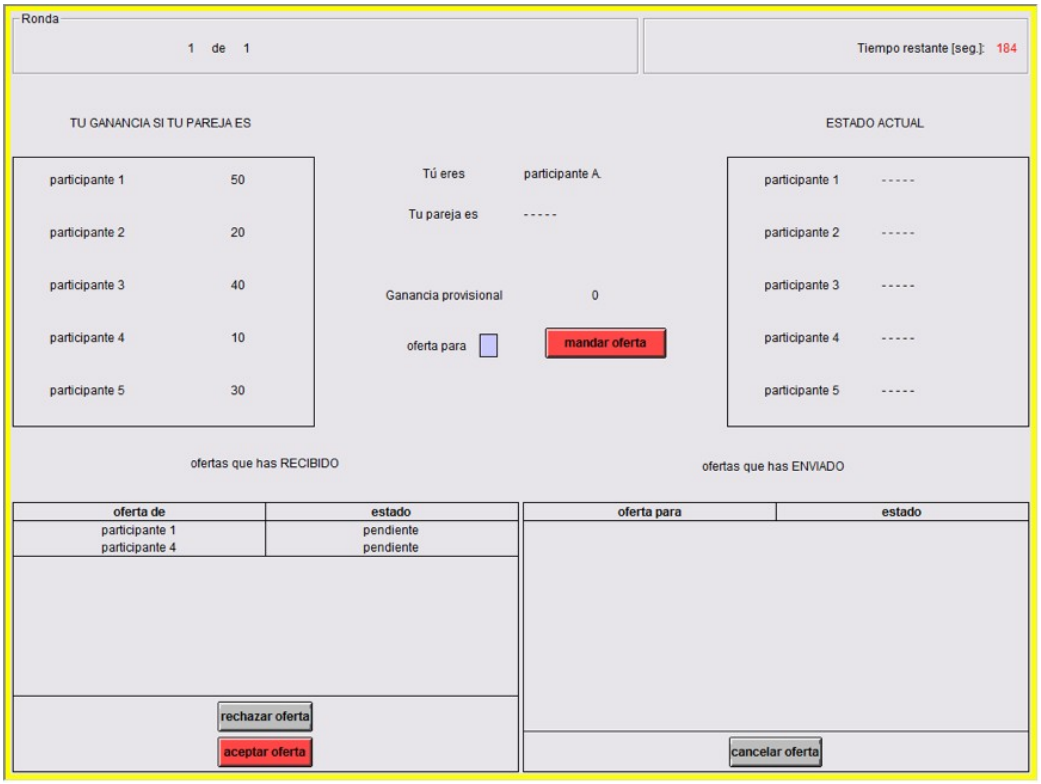
- Do not send, and do not accept any offer. This way you will remain alone, since each round starts with all participants being alone.
- You already have a partner, but she decides to leave you and to form a new partnership with somebody else from your group (or to stay alone).
- You already have a partner, but you send an offer to yourself and you accept it.

Each round lasts 4 minutes. Remember that your ID and your payoff table may change from round to round.

Payoffs

At the end of each round, the computer will display the status (the partner) of all members in your group, and will compute your earnings based on who your partner is. The sum of your earnings during the 15 rounds gives your final earnings. 35 EMU will be exchanged for 1 euro.

Figure 3: Sample screen



Payoff table for the QUESTIONNAIRE. Suppose that you are **Participant A**.

	PAYOFF for				
	Participant A	Participant B	Participant C	Participant D	Participant E
with Participant 1	**10**	40	20	50	20
with Participant 2	**20**	50	10	20	10
with Participant 3	**30**	20	50	40	40
with Participant 4	**40**	10	30	30	50
with Participant 5	**50**	30	40	10	30

	PAYOFF for				
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5
with **Participant A**	**10**	**30**	**50**	**40**	**30**
with Participant B	20	50	10	10	20
with Participant C	40	20	30	50	40
with Participant D	50	40	20	20	10
with Participant E	30	10	40	30	50

Table 1: ROUNDS 1, 2, 3, 4 and 5

	PAYOFF for				
	Participant A	Participant B	Participant C	Participant D	Participant E
with Participant 1	50	50	40	40	50
with Participant 2	20	40	50	50	40
with Participant 3	40	20	30	10	20
with Participant 4	10	30	20	30	10
with Participant 5	30	10	10	20	30

	PAYOFF for				
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5
with Participant A	50	50	40	40	50
with Participant B	20	40	50	50	40
with Participant C	40	20	10	20	30
with Participant D	10	30	30	10	20
with Participant E	30	10	20	30	10

Table 2: ROUNDS 6, 7, 8, 9 and 10

	PAYOFF for				
	Participant A	Participant B	Participant C	Participant D	Participant E
with Participant 1	10	20	10	20	10
with Participant 2	50	30	50	50	30
with Participant 3	40	50	40	30	50
with Participant 4	30	10	30	10	40
with Participant 5	20	40	20	40	20

	PAYOFF for				
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5
with Participant A	20	50	50	20	40
with Participant B	30	20	30	10	30
with Participant C	50	40	20	50	50
with Participant D	40	30	40	40	20
with Participant E	10	10	10	30	10

Table 3: ROUNDS 11, 12, 13, 14 and 15

	PAYOFF for				
	Participant A	Participant B	Participant C	Participant D	Participant E
with Participant 1	50	50	20	10	20
with Participant 2	20	40	10	20	10
with Participant 3	40	20	50	30	40
with Participant 4	10	30	40	50	30
with Participant 5	30	10	30	40	50

	PAYOFF for				
	Participant 1	Participant 2	Participant 3	Participant 4	Participant 5
with Participant A	50	40	10	20	10
with Participant B	40	30	20	10	20
with Participant C	10	50	30	40	50
with Participant D	30	20	50	30	40
with Participant E	20	10	40	50	30

Table 7: Proportion of naïve decisions made to the best available partner and to a partner better than the *status quo*

		TRT1	TRT2	TRT3	TRT4	TRT5	TRT6
S1	1	12%	24%	14%	7%	9%	15%
	2	53%	62%	84%	45%	68%	83%
	1 & 2	65%	86%	98%	52%	78%	99%
S2	1	13%	25%	18%	8%	10%	20%
	2	54%	61%	82%	44%	68%	80%
	1 & 2	67%	86%	100%	53%	78%	100%
S3	1	13%	25%	18%	9%	11%	20%
	2	56%	61%	82%	47%	69%	80%
	1 & 2	69%	86%	100%	56%	80%	100%
S4	1	38%	56%	–	34%	44%	–
	2	49%	42%	–	47%	50%	–
	1 & 2	87%	99%	–	81%	93%	–
S5	1	45%	58%	–	44%	46%	–
	2	47%	40%	–	44%	48%	–
	1 & 2	91%	99%	–	88%	95%	–
S6	1	49%	61%	–	53%	50%	–
	2	49%	39%	–	46%	48%	–
	1 & 2	98%	100%	–	99%	98%	–
A1	1	1%	1%	3%	2%	0%	1%
	2	76%	89%	96%	62%	79%	98%
	1 & 2	77%	91%	99%	64%	79%	100%
A2	1	1%	1%	3%	2%	0%	1%
	2	76%	89%	97%	63%	79%	99%
	1 & 2	77%	91%	100%	65%	79%	100%
A3	1	1%	1%	3%	2%	0%	1%
	2	79%	90%	97%	68%	81%	99%
	1 & 2	80%	91%	100%	70%	81%	100%
A4	1	1%	1%	–	4%	1%	–
	2	84%	96%	–	76%	90%	–
	1 & 2	85%	97%	–	80%	90%	–
A5	1	1%	1%	–	4%	1%	–
	2	83%	96%	–	77%	91%	–
	1 & 2	84%	97%	–	81%	91%	–
A6	1	3%	2%	–	5%	1%	–
	2	94%	97%	–	91%	96%	–
	1 & 2	97%	98%	–	97%	97%	–

NOTE. 1: better than the status quo; 2: best available partner. In TRT3 and TRT6, every subject in the market is single, so that the numbers for S4, S5, S6, A4, A5, and A6 are the same as for S1, S2, S3, A1, A2, and A3, respectively.

Table 8: Stability

	TRT1	TRT2	TRT3	TRT4	TRT5	TRT6
# stable	37	28	24	42	14	32
# abandoned stable	6	2	0	5	0	0
% abandoned stable	16%	7%	0%	12%	0%	0%
# final stable	31	26	24	37	14	32
% number-optimal	35%	31%	38%	32%	36%	31%
% letter-optimal	16%	4%	25%	16%	36%	19%
% compromise*	72%	98%	57%	77%	44%	75%
% final stable	69%	58%	53%	82%	31%	71%
# blocking pairs	0.8	1.4	0.6	0.3	1.4	0.4
time to first stable**	140	208	77	121	208	93
time to final stable**	147	212	77	124	208	93
duration of final stable**	93	28	164	116	32	147
# final Boston	10	7	6	12	11	15
% numbers proposing	100%	100%	88%	92%	64%	80%
% letters proposing	0%	0%	12%	8%	36%	20%

NOTE. *Average proportion of the compromise stable matching computed in those markets where it exists (in markets 1 and 3); **Average computed for those games in which a stable matching is reached.

Table 9: Efficiency

	TRT1	TRT2	TRT3	TRT4	TRT5	TRT6
% Pareto efficient final outcome	76%	64%	100%	91%	71%	98%
realized efficiency* (outcome)	88%	86%	92%	90%	90%	92%

NOTE. *As compared to the highest aggregated payoff possible (game 1: 360; game 2: 380; game 3: 410).