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Decentralized Matching Markets With(out) Frictions: A Laboratory Experiment

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Abstract

In a series of laboratory experiments, we explore the impact of different market features (the level of information, search costs, and the level of commitment) on agents' behaviour and on the outcome of decentralized matching markets. In our experiments, subjects on each side of the market actively search for a partner, make proposals, and are free to accept or reject any proposal received at any time throughout the game. Our results suggest that a low information level boosts market activity but does not affect stability or efficiency of the final outcome, unless coupled with search costs. Search costs have a significant negative impact on market activity, and on both stability and efficiency. Finally, commitment harms stability slightly but acts as a disciplinary device to market activity and is associated with higher efficiency levels of the final outcome.

Keywords: decentralized markets, two-sided matching, stability, efficiency, laboratory experiments.

JEL–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 agents must search actively, make and receive proposals, and eventually get matched to each other (be it to perform a task, a job or to trade goods) instead of submitting lists of preferences over potential partners to the matchmaker (as it happens in centralized markets).[1]

Given that stability is an essential characteristic of a desirable outcome in many centralized matching markets, the matching literature has mostly been concerned with guaranteeing stable outcomes. A stable matching is a matching that is individually rational; that is, each agent is matched to someone whom she finds better to being unmatched. In addition, a stable matching has no blocking pairs; in other words, there does not exist any pair of agents who are not matched to each other but would prefer to be so matched.

It is then by definition that we should not expect unstable matchings to survive if agents can interact freely in a decentralized market. In such settings we may even conjecture that a stable matching will ultimately prevail, since Roth and Vande Vate [25] have shown that starting with any matching there is a sequence of blocking pairs that, if satisfied, leads to a stable matching. Nevertheless, free interaction seldom occurs in decentralized markets. In fact, the cost of conducting partner search varies significantly across markets. The amount of time and money required to find the optimal partner, or even an acceptable one, ranges from negligible to important and may result in the premature end of partner search.[2] Moreover, agents' commitment to their matches depends on legal restrictions and social conventions. In some markets, face-to-face interaction between the two sides of the market, coupled with the fact that markets are small worlds, makes reneging on an accepted proposal very difficult. On the other hand, other markets have dimensions that render 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, are still open questions, both theoretically and empirically. Should we expect stability to be reached in decentralized markets? Even if we consider a frictionless market, where agents interact freely, agents are not automata and matching may not only occur among blocking pairs. Moreover, the level of information agents have

[1]In fully centralized two-sided matching markets, the matchmaker produces a matching of the two sides of the market using lists of preferences each agent submits for 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 of these are college admissions and the market for junior economists in the U.S.

[2]This has been explored in the search and matching literature (see Rogerson *et al.* [23]) and in the two-sided matching literature (Kagel and Roth [15], and Niederle and Roth [20]).

about the others (their preferences and their intentions), the cost of conducting partner search, and the level of commitment may dictate whether or not (only) blocking pairs resolve. It is sometimes the case that some blocking pairs do not resolve because the convergence process for some reason stops too early.

Our aim in this paper is to make a step forward in answering these questions using laboratory experiments to explore the impact of several market features on agents' strategies and the resulting final matching in decentralized markets. In our experiments, subjects on each side of the market, given their (strict cardinal) preferences, actively search for a matching partner from the other side of the market. We keep this search process essentially unconstrained, i.e. subjects are free to make proposals (although only one at a time) and are free to accept or reject any proposal received at any time throughout the game.[3] Moreover, partner search takes place under different scenarios that differ in market size and, more importantly, in the level of information subjects hold about 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 must leave the market).[4] Low information 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 emerge from our analysis. First, our results show that the intensity of market activity responds to the environment. In fact, taking the complete information, no-frictions scenario as benchmark, market activity, as measured by the average number of matching offers made, is higher under low information and when the market is large. In contrast, market activity is lower when offers are costly or commitment is in place (Result 1). However, while introducing cost to issuing proposals increases the acceptance rate and reduces the rejection rate with respect to the benchmark, commitment does not affect the rates of acceptance significantly (but does reduce the average number of acceptances). More important, commitment leads to a huge increase in the number of offers that are left unanswered and automatically cancelled when the agents involved leave the market. In other words, search costs seem to reduce the average number of offers, whereas commitment hinders acceptance. Therefore, the average number of acceptances is lower when commitment is in place, but it is higher when search is costly and when the market

[3]Given that the scarce experimental literature on decentralized matching markets does not agree on the design—and because of 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 [9].

[4]We also test markets that differ in complexity, as captured by the number of stable matchings and the number of rounds required for the deferred-acceptance algorithms—protocols that are used by matchmakers in various centralized markets to produce a matching—to converge under truth-telling. Given that we do not find significant or meaningful patterns along complexity, we do not emphasize it or consider it as a treatment variable.

is large (Result 2).

The average number of offers (and acceptances) depends on not only the environment, but also the identity of the recipients. For example, the proportion of offers made to matched individuals, particularly with whom the proposing subject does not form a blocking pair, is higher under incomplete information and lower when offers are costly. In fact, costly offers, particularly under complete information, lead to strategizing behavior: subjects, aware of the position they hold in the receivers' preferences, are more likely to propose to an agent who is single, unveiling their fear of rejection. In addition, the proportion of offers and acceptances that are myopically rational, i.e. that improve upon the status quo, also varies depending on the treatment. A large market size negatively affects both the proportion of myopically rational offers and acceptances, but cost has a positive effect on the proportion of myopically rational offers (Results 3a and 3b).

Where the features of the outcome are concerned, stable matchings are not the norm even in the absence of frictions, and it is only in small markets that stability—the rationale behind some centralized matching markets—acts as a very powerful driving force. Large markets show disappointingly low stability levels. Independently of market size, while stability is not sensitive to the information level, it is to other market characteristics: the proportion of stable final matchings is particularly low when search is costly and is also negatively affected, to a lesser extent, when commitment is combined with a large market size (Result 4). Surprisingly, and despite harming stability in some instances, commitment appears to boost efficiency. The treatments with commitment correspond to the highest proportions of matchings with high payoffs, whereas costly offers tend to decrease efficiency. Low information (unless combined with search costs) and a large market size do not affect efficiency significantly (Result 5).

To sum up, low information by itself does not seem to drive markets away from stability or efficiency. One possible explanation for this is that market activity is used to gather information. Nevertheless, when low information is combined with costly offers, which seriously hinders the number of offers, stability is severely affected and efficiency decreases. In fact, this friction affects not just the number of offers, but also the identity of the receivers. Commitment is associated with lower market activity levels and has a slight negative impact on stability, but it also acts as a disciplinary device, boosting efficiency.

In Section 2 we summarize the theoretical background of two-sided matching markets and provide a short review of the related literature. We describe the experimental design in Section 3. In Section 4 we lay out our hypotheses concerning subjects' behavior and the matching outcome and in Section 5 we summarize the main results of the experiments. Some concluding remarks follow in Section 6.

2 Theoretical background

2.1 Matching markets, stability, and the Gale-Shapley algorithm

A two-sided matching market consists of two disjoint sets of agents, and each agent is assumed to have preferences regarding 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 this paper we always refer to one-to-one matching, 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 it is individually rational and has no blocking pair, i.e. no pair of agents who would benefit from matching with one another over holding their current matches (or over being alone, in case they are not matched). Stability is an important concept in the matching literature as we only expect stable matchings to survive in frictionless markets. In fact, in the absence of transaction costs and of binding matching agreements, if a matching is unstable, there is at least one pair of unsatisfied agents who can easily match and circumvent the original matching.

Gale and Shapley [11] have shown that a stable matching exists for every matching market by means of the Gale-Shapley algorithm (henceforth the GS algorithm) that we describe as follows. Starting from a situation in which all agents are unmatched and given a profile of preferences every agent in one side of the market proposes to the best partner on her list of preferences in the first step of the algorithm. 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. The 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.[5] 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 optimal stable matching for the proposing side, 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 addition to each side's optimal stable matching, other stable matchings that represent a compromise between the two sides of the market may exist. In what follows, we refer to these matchings, when they exist, as *compromise* stable matchings.

In a centralized matching market each agent submits a list of preferences to the matchmaker who produces a matching by processing all lists by means of a matching algorithm. In many

[5] 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 deferred-acceptance algorithm.

successful real-life applications, the GS algorithm is used (see Roth [24]). In this paper we aim at exploring markets where matching is decentralized, i.e. where no matchmaker exists.

2.2 Literature review

The literature on decentralized two-sided matching markets is not large. The available theoretical work suggests that decentralized markets (in the absence of market frictions) settle at a stable matching. By solving a problem originally proposed by Knuth [16], Roth and Vande Vate [25] show that starting from any unstable matching, there exists a sequence of blocking pairs that, when successively satisfied, leads to stability. This implies that if blocking pairs are chosen randomly at each step, convergence to stability is guaranteed with probability one, however a number of related questions remain unanswered.

One such question concerns which stable matching is reached when more than one stable matching exists. Assuming that the starting point is the empty matching and that at each step blocking pairs are chosen uniformly at random—this is the so-called *random better response algorithm*—every stable matching can be reached with positive probability (since all pairs involved in a matching may be satisfied at the beginning of the process). Still, using simulations, Biró and Norman [2] show that some stable matchings are more likely than others.

Another question is the speed of convergence. Ackerman *et al.* [1] look into how fast the random better response algorithm converges to a stable matching and show that the expected convergence time to a stable matching is exponential in some matching markets but polynomial in others.[6] They propose an alternative best response algorithm, which exhibits similar worst-case behavior. Moreover, several simulations show that the degree of correlation and intercorrelation of preferences affects the speed of convergence. Celik and Knoblauch [6] show that in markets where agents on one side rank agents on the other side in a similar way, convergence is faster than when this is not the case. This behavior is also present in markets where participants prefer participants that prefer them (Boudreau and Knoblauch [4]).[7]

All of these results pertain to markets where agents are automata in the sense that they behave in a myopic way, forming a pair when both are better off. However, there are a few theoretical papers that analyze interaction among farsighted agents in decentralized matching markets. Pais [21] describes a sequential game where, at each point in time, one agent is able to make a matching offer and characterizes equilibrium outcomes, relating them to the stability concept. Haeringer and Wooders [12] and Diamantoudi *et al.* [7] also describe sequential matching games and show that introducing commitment may have a negative impact on the stability of matchings obtained in

[6] The latter class was later expanded in Hoffman *et al.* [14].

[7] See also Boudreau [3].

equilibrium. Finally, the role of transaction costs (modeled through discounting) and information is analyzed by Niederle and Yariv [19], where costly search combined with low information reduces the chances of obtaining a stable matching in equilibrium.

There also exist a few experimental papers on decentralized matching markets. Among these papers, Echenique and Yariv [8] 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. Contrary to our paper, information is complete in those experiments, making matching proposals is costless, and matching is not binding. Their results show that stability is a good predictor of market outcomes since 76% of their markets reach a stable matching. Moreover, in markets where agents have a compromise stable matching partner, that compromise stable matching is reached in 44% of all cases in which a stable matching is reached. Finally, Echenique and Yariv [8] also tested different cardinal representation of the same ordinal preferences and conclude that such representations have an impact on which matching is reached.[8]

The remaining list of experimental studies that look at decentralized matching markets is short and unrelated. In Haruvy and Ünver [13], a more rigid structure on the functioning of the market is imposed. 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, independent of the level of information subjects hold. Kagel and Roth [15] study the transition from a decentralized market where unraveling of transactions occurs in a centralized market. Nalbantian and Schotter [18] look at decentralized matching procedures when agents' payoffs constitute private information. Niederle and Roth [20] 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—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 [9], and Molis and Veszteg [17]) approach one-sided matching markets.

3 Experimental design

3.1 Experimental treatments and matching markets

Conditions in our experimental treatments vary along the following lines: the (in)existence of a *friction*, the level of information subjects have about the preferences of the others, and the size of

[8]We present a more detailed comparison between Echenique and Yariv [8] and this paper in the concluding section, addressing both experimental designs and results.

the matching market.

The frictions we consider are of two types: it can be costly to issue a proposal, or it may be the case that there is commitment. In treatments where conducting partner search is costly, each offer has a fixed cost that subjects pay from their initially allocated budget, which is large enough to avoid bankruptcies.[9] On the other hand, in treatments with commitment, acceptance is binding, so that couples leave the market once matched. In no-friction treatments, issuing offers is costless and there is no commitment, so that matched agents stay in the market, continue sending and receiving offers, and eventually re-match, leaving the abandoned partner alone.

Where information of others' preferences is concerned, we consider two levels: low information environments where participants' preference profiles are private information and high information environments where participants know the entire preference profile.[10]

Finally, we consider two different market sizes. Small treatments have ten subjects—five on each side of the market, represented by numbers from 1 to 5 and by letters from a to e—whereas large treatments are twice as big with twenty subjects—ten on each side of the market, labelled from 1 to 10 and from a to j.

Overall this results in a 3×2×2 design: (no-friction, costly offers, commitment)×(low information, high information)×(small market, large market). In what follows, we usually take the no-friction, high information, small market treatment as benchmark or baseline treatment.

In each treatment, participants played under three different preference profiles that differ in two dimensions. First, the level of conflict (and therefore complexity), as measured by the size of the set of stable matchings, varies across markets. Small markets, labelled S-A, S-B, and S-C, have two or three stable matchings, whereas large markets, labelled L-A, L-B, and L-C, have four or seven stable matchings. Second, markets also differ in the number of steps it takes for the GS algorithms to converge to a stable matching under truth-telling. 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 S-A, S-B, and S-C, respectively. It takes 7, 11, and 3 steps for the GS algorithm with letters proposing to converge and 9, 9, and 5 steps with numbers proposing to converge in markets L-A, L-B, and L-C, respectively.

Table 1 and Table 2 contain the preference profiles and a summary of their features. Note that large markets have some resemblance to small markets. Namely, market L-A consists of two embedded markets S-A—one market composed of agents 1 to 5 and a to e and the other composed

[9] The per-offer cost was 4 Experimental Monetary Units (EMU) for an initial budget of 16 EMU. The part of the budget that is not spent on sending offers is 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.

[10] In low information environments, each subject knows her own payoff table and knows that the others' "are similar." We do not specify any probability distribution or upper and lower limits for the others' valuations.

of agents 6 to 10 and f to j—so that in any stable matching of market L-A, each agent is matched to someone who belongs to the same market-component. The same relation holds between markets L-B and S-B, and between markets L-C and S-C.

LETTER	$. \succ . \succ . \succ . \succ .$	NUMBER	$. \succ . \succ . \succ . \succ .$	STABLE MATCHINGS [# GS STEPS]		
			MARKET S-A			
a	$1 \succ 3 \succ 5 \succ 2 \succ 4$	1	$a \succ c \succ e \succ b \succ d$	LETTER-OPTIMAL	$(1a, 2b, 3c, 4d, 5e)$	[3]
b	$1 \succ 2 \succ 4 \succ 3 \succ 5$	2	$a \succ b \succ d \succ c \succ e$		$(1a, 2b, 3e, 4c, 5d)$	
c	$2 \succ 1 \succ 3 \succ 4 \succ 5$	3	$b \succ a \succ d \succ e \succ c$	NUMBER-OPTIMAL	$(1a, 2b, 3d, 4e, 5c)$	[3]
d	$2 \succ 1 \succ 4 \succ 5 \succ 3$	4	$b \succ a \succ e \succ c \succ d$			
e	$1 \succ 2 \succ 5 \succ 3 \succ 4$	5	$a \succ b \succ c \succ d \succ e$			
			MARKET S-B			
a	$2 \succ 3 \succ 4 \succ 5 \succ 1$	1	$c \succ d \succ b \succ a \succ e$	LETTER-OPTIMAL	$(1e, 2a, 3b, 4c, 5d)$	[6]
b	$3 \succ 5 \succ 2 \succ 1 \succ 4$	2	$a \succ c \succ d \succ b \succ e$	NUMBER-OPTIMAL	$(1e, 2a, 3d, 4c, 5b)$	[5]
c	$2 \succ 3 \succ 4 \succ 5 \succ 1$	3	$a \succ d \succ b \succ c \succ e$			
d	$2 \succ 5 \succ 3 \succ 1 \succ 4$	4	$c \succ d \succ e \succ a \succ b$			
e	$3 \succ 4 \succ 2 \succ 5 \succ 1$	5	$c \succ a \succ b \succ d \succ e$			
			MARKET S-C			
a	$1 \succ 3 \succ 5 \succ 2 \succ 4$	1	$a \succ b \succ d \succ e \succ c$	LETTER-OPTIMAL	$(1a, 2b, 3c, 4d, 5e)$	[2]
b	$1 \succ 2 \succ 4 \succ 3 \succ 5$	2	$c \succ a \succ b \succ d \succ e$		$(1a, 2b, 3e, 4c, 5d)$	
c	$3 \succ 4 \succ 5 \succ 1 \succ 2$	3	$d \succ e \succ c \succ b \succ a$	NUMBER-OPTIMAL	$(1a, 2b, 3d, 4e, 5c)$	[3]
d	$4 \succ 5 \succ 3 \succ 2 \succ 1$	4	$e \succ c \succ d \succ a \succ b$			
e	$5 \succ 3 \succ 4 \succ 1 \succ 2$	5	$c \succ d \succ e \succ b \succ a$			

Table 1: Small markets S-A to S-C. Preference profiles, stable matchings, and number of steps the GS algorithms take to converge.

3.2 Procedures

Our experiment was conducted at LINEEX at the University of Valencia, with 420 students recruited online, by using the z-Tree software (Fischbacher [10]).[11] At the beginning of each session, printed instructions were given to subjects and 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 works. The English translation of the instructions along with a sample of the screen that participants would see can be found in Appendix A.

Each treatment was conducted in a separate session. Subjects participated in one session only. Each session entailed one practice round and several paying rounds. In small treatments, subjects played each market S-A, S-B, and S-C five times in a row (fifteen paying rounds in total), whereas in large treatments subjects played markets L-A, L-B, and L-C three times in a row (nine paying rounds in total). In each round, subjects played in a randomly assigned role (and ID).

[11]Small market treatments involved 180 subjects and took place in May 2010. Large market treatments involved 240 subjects and were conducted in December 2012.

LETTER	. ≻ . ≻ . ≻ . ≻ . ≻ . ≻ . ≻ . ≻ . ≻ .	NUMBER	. ≻ . ≻ . ≻ . ≻ . ≻ . ≻ . ≻ . ≻ . ≻ .	STABLE MATCHINGS [# GS STEPS]		
		MARKET L-A				
a	1 ≻ 6 ≻ 3 ≻ 8 ≻ 5 ≻ 10 ≻ 2 ≻ 7 ≻ 4 ≻ 9	1	a ≻ f ≻ c ≻ h ≻ e ≻ j ≻ b ≻ g ≻ d ≻ i	LETTER-OPTIMAL	(1a,2b,3c,4d,5e,6f,7g,8h,9i,10j)	[7]
b	1 ≻ 6 ≻ 2 ≻ 7 ≻ 4 ≻ 9 ≻ 3 ≻ 8 ≻ 5 ≻ 10	2	a ≻ f ≻ b ≻ g ≻ d ≻ i ≻ c ≻ h ≻ e ≻ j		(1a,2b,3c,4d,5e,6f,7g,8j,9h,10i)	
c	2 ≻ 7 ≻ 1 ≻ 6 ≻ 3 ≻ 8 ≻ 4 ≻ 9 ≻ 5 ≻ 10	3	b ≻ g ≻ a ≻ f ≻ d ≻ i ≻ e ≻ j ≻ c ≻ h		(1a,2b,3e,4c,5d,6f,7g,8h,9i,10j)	
d	2 ≻ 7 ≻ 1 ≻ 6 ≻ 4 ≻ 9 ≻ 5 ≻ 10 ≻ 3 ≻ 8	4	b ≻ g ≻ a ≻ f ≻ e ≻ j ≻ c ≻ h ≻ d ≻ i		(1a,2b,3e,4c,5d,6f,7g,8i,9j,10h)	
e	1 ≻ 6 ≻ 2 ≻ 7 ≻ 5 ≻ 10 ≻ 3 ≻ 8 ≻ 4 ≻ 9	5	a ≻ f ≻ b ≻ g ≻ c ≻ h ≻ d ≻ i ≻ e ≻ j		(1a,2b,3e,4c,5d,6f,7g,8j,9h,10i)	
f	6 ≻ 1 ≻ 8 ≻ 3 ≻ 10 ≻ 5 ≻ 7 ≻ 2 ≻ 9 ≻ 4	6	f ≻ a ≻ h ≻ c ≻ j ≻ e ≻ g ≻ b ≻ i ≻ d		(1a,2b,3d,4e,5c,6f,7g,8j,9h,10i)	
g	6 ≻ 1 ≻ 7 ≻ 2 ≻ 9 ≻ 4 ≻ 8 ≻ 3 ≻ 10 ≻ 5	7	f ≻ a ≻ g ≻ b ≻ i ≻ d ≻ h ≻ c ≻ j ≻ e	NUMBER-OPTIMAL	(1a,2b,3d,4e,5c,6f,7g,8i,9j,10h)	[9]
h	7 ≻ 2 ≻ 6 ≻ 1 ≻ 8 ≻ 3 ≻ 9 ≻ 4 ≻ 10 ≻ 5	8	g ≻ b ≻ f ≻ a ≻ i ≻ d ≻ j ≻ e ≻ h ≻ c			
i	7 ≻ 2 ≻ 6 ≻ 1 ≻ 9 ≻ 4 ≻ 10 ≻ 5 ≻ 8 ≻ 3	9	g ≻ b ≻ f ≻ a ≻ j ≻ e ≻ h ≻ c ≻ i ≻ d			
j	6 ≻ 1 ≻ 7 ≻ 2 ≻ 10 ≻ 5 ≻ 8 ≻ 3 ≻ 9 ≻ 4	10	f ≻ a ≻ g ≻ b ≻ h ≻ c ≻ i ≻ d ≻ j ≻ e			
		MARKET L-B				
a	2 ≻ 7 ≻ 3 ≻ 8 ≻ 4 ≻ 9 ≻ 5 ≻ 10 ≻ 1 ≻ 6	1	c ≻ h ≻ d ≻ i ≻ b ≻ g ≻ a ≻ f ≻ e ≻ j	LETTER-OPTIMAL	(1e,2a,3b,4c,5d,6j,7f,8g,9h,10i)	[11]
b	3 ≻ 8 ≻ 5 ≻ 10 ≻ 2 ≻ 7 ≻ 1 ≻ 6 ≻ 4 ≻ 9	2	a ≻ f ≻ c ≻ h ≻ d ≻ i ≻ b ≻ g ≻ e ≻ j		(1e,2a,3b,4c,5d,6j,7f,8i,9h,10g)	
c	2 ≻ 7 ≻ 3 ≻ 8 ≻ 4 ≻ 9 ≻ 5 ≻ 10 ≻ 1 ≻ 6	3	a ≻ f ≻ d ≻ i ≻ b ≻ g ≻ c ≻ h ≻ e ≻ j		(1e,2a,3d,4c,5b,6j,7f,8g,9h,10i)	
d	2 ≻ 7 ≻ 5 ≻ 10 ≻ 3 ≻ 8 ≻ 1 ≻ 6 ≻ 4 ≻ 9	4	c ≻ h ≻ d ≻ i ≻ e ≻ j ≻ a ≻ f ≻ b ≻ g	NUMBER-OPTIMAL	(1e,2a,3d,4c,5b,6j,7f,8i,9h,10g)	[9]
e	3 ≻ 8 ≻ 4 ≻ 9 ≻ 2 ≻ 7 ≻ 5 ≻ 10 ≻ 1 ≻ 6	5	c ≻ h ≻ a ≻ f ≻ b ≻ g ≻ d ≻ i ≻ e ≻ j			
f	7 ≻ 2 ≻ 8 ≻ 3 ≻ 9 ≻ 4 ≻ 10 ≻ 5 ≻ 6 ≻ 1	6	h ≻ c ≻ i ≻ d ≻ g ≻ b ≻ f ≻ a ≻ j ≻ e			
g	8 ≻ 3 ≻ 10 ≻ 5 ≻ 7 ≻ 2 ≻ 6 ≻ 1 ≻ 9 ≻ 4	7	f ≻ a ≻ h ≻ c ≻ i ≻ d ≻ g ≻ b ≻ j ≻ e			
h	7 ≻ 2 ≻ 8 ≻ 3 ≻ 9 ≻ 4 ≻ 10 ≻ 5 ≻ 6 ≻ 1	8	f ≻ a ≻ i ≻ d ≻ g ≻ b ≻ h ≻ c ≻ j ≻ e			
i	7 ≻ 2 ≻ 10 ≻ 5 ≻ 8 ≻ 3 ≻ 6 ≻ 1 ≻ 9 ≻ 4	9	h ≻ c ≻ i ≻ d ≻ j ≻ e ≻ f ≻ a ≻ g ≻ b			
j	8 ≻ 3 ≻ 9 ≻ 4 ≻ 7 ≻ 2 ≻ 10 ≻ 5 ≻ 6 ≻ 1	10	h ≻ c ≻ f ≻ a ≻ g ≻ b ≻ i ≻ d ≻ j ≻ e			
		MARKET L-C				
a	1 ≻ 6 ≻ 3 ≻ 8 ≻ 5 ≻ 10 ≻ 2 ≻ 7 ≻ 4 ≻ 9	1	a ≻ f ≻ b ≻ g ≻ d ≻ i ≻ e ≻ j ≻ c ≻ h	LETTER-OPTIMAL	(1a,2b,3c,4d,5e,6f,7g,8h,9i,10j)	[3]
b	1 ≻ 6 ≻ 2 ≻ 7 ≻ 4 ≻ 9 ≻ 3 ≻ 8 ≻ 5 ≻ 10	2	c ≻ h ≻ a ≻ f ≻ b ≻ g ≻ d ≻ i ≻ e ≻ j		(1a,2b,3c,4d,5e,6f,7g,8j,9h,10i)	
c	3 ≻ 8 ≻ 4 ≻ 9 ≻ 5 ≻ 10 ≻ 1 ≻ 6 ≻ 2 ≻ 7	3	d ≻ i ≻ e ≻ j ≻ c ≻ h ≻ b ≻ g ≻ a ≻ f		(1a,2b,3e,4c,5d,6f,7g,8h,9i,10j)	
d	4 ≻ 9 ≻ 5 ≻ 10 ≻ 3 ≻ 8 ≻ 2 ≻ 7 ≻ 1 ≻ 6	4	e ≻ j ≻ c ≻ h ≻ d ≻ i ≻ a ≻ f ≻ b ≻ g		(1a,2b,3e,4c,5d,6f,7g,8i,9j,10h)	
e	5 ≻ 10 ≻ 3 ≻ 8 ≻ 4 ≻ 9 ≻ 1 ≻ 6 ≻ 2 ≻ 7	5	c ≻ h ≻ d ≻ i ≻ e ≻ j ≻ b ≻ g ≻ a ≻ f		(1a,2b,3e,4c,5d,6f,7g,8j,9h,10i)	
f	6 ≻ 1 ≻ 8 ≻ 3 ≻ 10 ≻ 5 ≻ 7 ≻ 2 ≻ 9 ≻ 4	6	f ≻ a ≻ g ≻ b ≻ i ≻ d ≻ j ≻ e ≻ h ≻ c		(1a,2b,3d,4e,5c,6f,7g,8j,9h,10i)	
g	6 ≻ 1 ≻ 7 ≻ 2 ≻ 9 ≻ 4 ≻ 8 ≻ 3 ≻ 10 ≻ 5	7	h ≻ c ≻ f ≻ a ≻ g ≻ b ≻ i ≻ d ≻ j ≻ e	NUMBER-OPTIMAL	(1a,2b,3d,4e,5c,6f,7g,8i,9j,10h)	[5]
h	8 ≻ 3 ≻ 9 ≻ 4 ≻ 10 ≻ 5 ≻ 6 ≻ 1 ≻ 7 ≻ 2	8	i ≻ d ≻ j ≻ e ≻ h ≻ c ≻ g ≻ b ≻ f ≻ a			
i	9 ≻ 4 ≻ 10 ≻ 5 ≻ 8 ≻ 3 ≻ 7 ≻ 2 ≻ 6 ≻ 1	9	j ≻ e ≻ h ≻ c ≻ i ≻ d ≻ f ≻ a ≻ g ≻ b			
j	10 ≻ 5 ≻ 8 ≻ 3 ≻ 9 ≻ 4 ≻ 6 ≻ 1 ≻ 7 ≻ 2	10	h ≻ c ≻ i ≻ d ≻ j ≻ e ≻ g ≻ b ≻ f ≻ a			

Table 2: Large markets L-A to L-C. Preference profiles, stable matchings, and number of steps the GS algorithms take to converge.

At the beginning of each round, the computer randomly assigned subjects to groups of ten in small treatments and to groups of twenty in large treatments and, within each group, sorted them into two sets, numbers and letters. We used anonymous stranger matching, i.e. participants were were informed that both groups and number/letter sets change randomly throughout the session, and participants were not informed about who the other members of their group were.

Subjects were not allowed to communicate with each other, other than sending and deciding over offers on the screen. At any time throughout the game a subject could issue offers to any participant on the other side of the market, i.e. in the other set of the same group, or respond to proposals received. However, a participant could only make one offer at a time. In no-commitment treatments this means that a participant could not send a new offer until the previous one had been either accepted or rejected by the other participant, or withdrawn by the sender. In commitment treatments, since acceptance results in the matched couple leaving the market, a participant could only send a new offer once the previous one had been rejected or withdrawn.

The status of an offer could therefore be pending (sent, but not accepted or rejected), accepted, rejected, or withdrawn (by the sender). In no-commitment treatments, 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 sent offer). Finally, in order to keep the amount of real-time information on screen manageable (and because it resembles reality better), a participant would only receive information on the status of the offers that she made and received, and on the current matching in her market.

In small treatments, each round had a fixed duration of 4.5 minutes, whereas in large treatments each round had a maximum duration of 8 minutes and it would automatically end after 30 seconds of inactivity.[12] Sessions lasted 90 minutes on average. At the end of a 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.[13] These payoffs were similar across subjects in the same treatment. In small treatments, 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. In large treatments, every subject got 100 EMU for the top choice, 90 for the second choice, 80 for the third, etc., and 0 when she ended up alone. The final payoff of the session was computed as the accumulated payoff over all paying rounds and amounted to 15€ for the average subject in both the small and the large treatments, including a show-up fee.[14]

Table 3 below contains a summary of all treatments. In total, six out of twelve sessions correspond to small treatments (treatments S1 to S6), combining a high or low information level with the no-friction, costly offers, and commitment scenarios. The remaining six sessions correspond to large treatments, with the same combinations of information level and frictions (treatments L1 to L6).

	ALL TREATMENTS					
MARKET ACTIVITY	both sides offer					
TIMING	real-time action					
# OF OFFERS	one at a time					
	S TREATMENTS			L TREATMENTS		
GROUP SIZE	5 + 5			10 + 10		
ROUNDS	(1) + 3×5			(1) + 3×3		
PREFERENCE PROFILES	2 or 3 stable matchings			4 or 7 stable matchings		
# OF SUBJECTS PER SESSION	30			40		
	S1/S4	S2/S5	S3/S6	L1/L4	L2/L5	L3/L6
FRICTION	no	costly offers	commitment	no	costly offers	commitment
INFORMATION	low/high	low/high	low/high	low/high	low/high	low/high

Table 3: Treatment summary.

[12] The addition of this flexible ending rule in the large and longer treatments aimed at shortening idle time. We do not believe that it had any significant impact on individual behavior or the final outcome.

[13] In treatments where rematches are allowed, this rule implies that the intermediate matches are worthless. It is as if they belonged to an interview phase.

[14] In small treatments subjects received 1€ per 35 EMU, whereas in large treatments subjects received 1€ per 40 EMU.

4 Hypotheses

In this section, based on intuition and the few existing theoretical results, we formulate our hypotheses concerning subjects' behavior and stability of the final outcome.

Our first hypothesis concerns the number of proposals made per subject on average, which we use as a measure of the level of market activity. We rely on intuition only since there are, to the best of our knowledge, no theoretical results on how market activity in decentralized matching markets is affected by information and the existence of market frictions. Therefore, taking the frictionless treatments with complete information as a benchmark, we expect the number of proposals to be higher when subjects have no information on others' preferences. Under complete information, a subject can check before issuing a proposal whether the intended recipient is actually matched to someone she finds better than the proposer and many proposals that are sent under incomplete information may be considered unworthy when information is complete. On the other hand, under incomplete information offers can be used as a means to extract information: subjects may issue proposals to locate the position they occupy in their potential partners' lists.

The same effect is expected to hold independently of market size and, perhaps to a lesser extent, in the presence of frictions. In fact, when search costs exist or commitment is present, we expect that the decision of issuing an offer is less automatic and more considered than in baseline treatments. In the former case, it is because there is an obvious opportunity cost to issuing an offer, while in the latter case it is because in case the offer is accepted, the resulting match is permanent.[15] Moreover, these arguments hold independently of the level of information and market size. So, we may expect both frictions—search costs and commitment—to reduce market activity under the two levels of information and for both market sizes.

Finally, given that in large markets there are twice as many potential partners as in the small markets, market activity should increase with market size. This increase in market activity may, nevertheless, be less than proportional to the increase in market size due to subjects' limited capability to handle the increase in complexity that results. Hypothesis 1 summarizes the above argument in terms of subjects' activity. Note that it could be easily rephrased for the market level by taking into consideration the number of subjects on the market in each treatment.

Hypothesis 1. *The number of offers per subject is higher under incomplete than under complete information, and it is higher in large markets than in small markets. When compared to the no-friction treatments, the number of offers per subject is lower in the presence of cost and commitment.*

[15] In the commitment treatments, the number of offers may be smaller not only because irreversibility makes subjects give their decisions a second thought, but also simply by construction, since once a subject is matched, she leaves the market and thus cannot issue any more proposals.

How differences in the number of offers are reflected in the number of deals depends on the acceptance rate. Given that in treatments with commitment acceptance implies leaving the market immediately, we expect treatments with commitment to exhibit the lowest average acceptance rates.[16] However, there is no clear intuition to how or even whether the acceptance rate is supposed to change with the level of information, with the introduction of cost, or with market size. This is why our Hypothesis 2 includes weak statements based on Hypothesis 1.

Hypothesis 2. *The number of acceptances per subject is weakly higher under incomplete than under complete information and it is weakly higher in large than in small markets. When compared to the no-friction treatments, the number of acceptances per subject is weakly lower in the presence of cost and it is lower when there is commitment.*

Clearly, market features can affect not only the volume of offers, but also their timing and the identity of the recipients. For instance, take the case of *myopically rational offers*, i.e. offers made to agents that are better than one's current partner. Those offers that fail this requirement are clearly not consistent with acting straightforwardly according to one's true preferences. Similarly, *myopically rational acceptances* refers to acceptance decisions that improve upon the *status quo*, i.e., the acceptance of an offer from an agent that is ranked better than the current partner. Given these definitions, it follows that a *blocking pair* is satisfied when a myopically rational offer is responded with a myopically rational acceptance.

In treatments with commitment, all offers and acceptances are myopically rational by design, as every agent in the market starts unmatched, leaves the market upon acceptance, and finds each potential partner acceptable. In the absence of commitment, the only explanation that emerges for a rational individual's behavior of not meeting myopic rationality is that it is part of a sophisticated, farsighted strategy. It follows that in treatments with incomplete information, where there is hardly any information to strategize on, it is hard to imagine that offers and acceptance decisions are actually motivated by farsighted behavior, so that, if anything, we expect the proportion of myopically rational offers and acceptances per subject to be higher when information is incomplete. In what market size is concerned, a large market size may contribute to reducing the ability to recognize a strategizing opportunity, in such a way that, if anything, it should have a positive effect on myopically rational behavior. Finally, when offers are costly, strategizing comes at a higher cost and subjects may be inclined to think their offer decisions through, whereas there is no predictable impact on myopically rational acceptance. Since there is no reason to believe that these influences are actually significant, we summarise this discussion in Hypothesis 3 as follows.

[16]In fact, by construction, in treatments with commitment, the maximum possible average number of accepted offers per subject equals 0.5.

Hypothesis 3. *The proportion of deals that correspond to satisfying blocking pairs is weakly higher when information is incomplete than when information is complete, and weakly higher when the market size is large. The proportion of deals that correspond to satisfying blocking pairs is maximal when there is commitment. When compared to the no-friction treatments, the proportion of deals that correspond to satisfying blocking pairs is weakly higher in the presence of cost.*

A related question is whether all blocking pairs disappear at some point, i.e., whether convergence to stability occurs and how this depends on market features. Roth and Vande Vate [25] have shown that starting at any matching, there is at least one sequence of satisfied blocking pairs that leads to a stable matching, so that if all blocking pairs have positive probability of resolving, a stable matching is obtained with probability one. Therefore, according to theory, in the absence of frictions, we may expect agents that act in a myopically rational way and that exhaust all opportunities to reach a stable matching.

Nevertheless, agents may act strategically, so that pairs other than blocking pairs may form in a decentralized matching market like the one we are testing in the lab. And, as suggested in the discussion that precedes Hypothesis 3, the level of strategizing may be affected by information and the existence of frictions. On the other hand, even if all agents send out and accept offers in a myopically rational way, they may reject offers from or refrain from sending out all offers to blocking partners. One possible reason for this is the existence of frictions that may dictate the premature end of partner search, so that blocking pairs are left unmatched. The case is clear for commitment, whereby even though all offers and acceptances are myopically rational by construction, agents leave the market as they match, so that bad decisions taken early in the matching process are irreversible and many blocking pairs may remain unresolved. And theory supports this: in Haeringer and Wooders [12] and Diamantoudi *et al.* [7], commitment drives the equilibrium outcomes away from stability. Where cost is concerned, Niederle and Yariv [19] show that, in certain environments, the cost of searching for a partner negatively affects stability when information is low. In light of Hypotheses 1 and 2, this may be explained by a reduced level of market activity when search is costly. In what information and market size are concerned, the effects on stability are ambiguous. Even though, according to Hypotheses 1 and 2, the level of market activity may be higher in large markets, it is probably the case that this difference in the number of deals is not proportional to the difference in market size, so that it may be harder to find the path to stability. Also, providing agents with complete information on others' preferences can contribute, in light of Hypothesis 3, to a lower frequency of deals that correspond to satisfying blocking pairs when compared to the incomplete information treatments. But, on the other hand, complete information allows each agent to detect partners with whom she forms a blocking pair with ease. Still, low information and a large market size should not prevent blocking pairs from resolving and a stable matching from being reached, and therefore should not represent a departure from the theoretical model, unless the matching process ends prematurely, which is only prone to happen in the presence of frictions. We summarize in the following hypothesis.

Hypothesis 4. *In the complete information, no-friction treatments all outcomes are stable. The level of information and market size do not affect the proportion of stable outcomes significantly. Moreover, when compared to the no-friction treatments, treatments with a positive cost of conducting partner search and with commitment present a lower proportion of stable outcomes.*

In a two-sided matching market, stability and efficiency are closely related as every stable matching is Pareto efficient. In this paper, however, the proxy we use to evaluate efficiency is the fraction of the available surplus that is captured by agents, so that the level of efficiency of a matching is the corresponding sum of payoffs as a percentage of the maximum achievable payoff in the corresponding market. In the analysis that follows, we classify matchings into two groups: "efficient" matchings deliver a level of efficiency of at least 80% and "non-efficient" matchings have lower levels of efficiency. Since each stable matching in all markets we consider corresponds to efficiency levels higher than this threshold, all stable matchings are efficient according to our definition.[17] Our Hypothesis 5 on efficiency therefore follows from Hypothesis 4.[18]

Hypothesis 5. *In the complete information, no-friction treatments all outcomes are efficient. The level of information and market size do not affect the proportion of efficient matchings significantly.*

5 Results

We now present the results of our experiment. First, we are interested in how market activity and behavior are affected by different market features (Section 5.1). Afterwards, we study the implications of individual behavior on stability (Section 5.2) and efficiency (Section 5.3).

5.1 Market activity

Our first results concern market activity. Since we could not discover any meaningful difference in behavior or market outcomes induced by the different preference profiles, for the sake of a more

[17]Stable matchings in markets S-A, S-B, and S-C achieve efficiency levels of 83.3%, 89.5%, and 100%, respectively. The numbers are identical for large markets. That is, stable matchings in markets L-A, L-B, and L-C achieve efficiency levels of 83.3%, 89.5%, and 100%. Note that, unlike the Gale-Shapley algorithm for stability, there does not exist an elegant way to find all the Pareto-efficient or the payoff-maximizing allocations. With the help of the computer we have studied all possible matchings, and have found 360, 380, and 410 as the largest possible aggregate payoff for markets S-A, S-B, and S-C, and 1440, 1520, and 1640 for markets L-A, L-B, and L-C, respectively.

[18]No predictions with respect to the impact of cost and commitment are made since Hypothesis 4 predicts that full stability is not achieved and failure to meet stability does not imply that a matching is not efficient.

focused analysis on market frictions, market size, and information, we present results from the pooled database (the three profiles together) across experimental treatments. Table 4 shows levels of market activity.[19]

TREATMENT	S1	S2	S3	S4	S5	S6	L1	L2	L3	L4	L5	L6
	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$
	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$
	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST
	LRG	LRG	LRG	LRG	LRG	LRG	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$
ROUND AVERAGES												
OFFERS	21.56	9.89	14.53	30.31	12.67	15.96	73.89	27.61	35.78	111.06	40.39	49.22
ACCEPTANCES	6.98	5.62	5.00	9.13	6.44	4.98	22.06	13.00	10.00	26.11	16.28	10.00
REJECTIONS	3.27	1.24	0.91	7.13	1.62	1.24	15.17	4.67	3.11	28.83	6.50	5.17
CANCELLATIONS	7.67	1.82	0.98	10.09	2.84	1.02	31.56	7.89	4.56	48.56	12.67	12.39
ROUND RATES												
ACCEPTANCE	33%	63%	36%	31%	52%	33%	31%	49%	29%	24%	41%	22%
REJECTION	15%	11%	6%	24%	11%	7%	20%	16%	8%	25%	16%	10%
CANCELLATION	35%	16%	6%	32%	22%	7%	42%	28%	13%	44%	31%	25%
NO RESPONSE	17%	10%	52%	13%	15%	53%	7%	7%	50%	7%	12%	43%

Table 4: Market activity per treatment. Per-round average number of offers, acceptances, rejections, cancellations; and per-round average rates of acceptance, rejection, cancellation, and no response.

Depending on the treatment, in each round of play, there were between approximately 10 and 30 offers in the small treatments and between 28 and 111 offers in the large treatments. These numbers appear to confirm Hypothesis 1, as size affects the average number of offers and treatments under incomplete information exhibit higher average numbers of offers when compared to the corresponding treatments with complete information, particularly in the absence of frictions. This effect is less striking when incomplete information is combined with costly offers or with commitment as both frictions increase the cost of such behavior. Moreover, both costly offers and commitment *per se* appear to discipline behavior in the sense that the average numbers of offers in the treatments with frictions are significantly lower than in the baseline treatments, particularly when offers become costly. Additionally, cancellation rates fall significantly in both cases, suggesting that offers are better thought through, particularly when commitment is introduced.

It is interesting to note that, when offers are costly, a bigger proportion of offers made is actually acceptable (and ends up being accepted), whereas the rejection rate falls. This appears to reflect a less erratic behaviour when issuing proposals is costly. Nevertheless, introducing commitment has a different effect on reaction rates: acceptance rates do not present significant change, explicit

[19] Average numbers were obtained counting, in each round and for each group separately, all offers, acceptances, rejections, and cancellations, respectively, and then computing the average. Offers that were automatically cancelled, i.e. offers that were left unanswered when the market ended or, in the treatments with commitment, when either the sender or the recipient leave the market, are not counted. This is the reason why the sum of the acceptance, rejection, and cancellation rates is always smaller than one.

rejection rates fall in most cases, but a huge proportion of offers (approximately 50% in each treatment with commitment) are left unresponded to and are automatically cancelled once the proposer leaves the market.

Differences in the acceptance rate together with differences in the average numbers of offers translate into differences in the average number of acceptances in most cases along the lines of Hypothesis 2. In fact, incomplete information and a large market size appear to deliver a higher average number of acceptances. Additionally, search cost reduces the average number of acceptances (while significantly increasing the acceptance rate), which achieves its lowest levels with commitment (even though acceptance rates are roughly the same with commitment as in the baseline treatments). In fact, since accepting an offer implies abandoning the market, each subject can accept at most one proposal by construction.

To better tackle market activity and to perform statistical comparisons across treatments, we run (ordinary-least-squares) regressions taking as dependent variables the average number of offers (regression 1) and the average number of acceptances (regression 2). The independent variables are dummies indicating the level of information, the existence of commitment or search cost, and the size of the market, as well as the number of periods. Period is a counter for the number of rounds or games played, capturing experience.[20] In specification 2 we additionally include the number of offers as a regressor, since the number of acceptances is naturally bounded by the number of offers.

Market activity	Offers reg. 1	Acceptances reg. 2
period	-0.9651***	0.1019***
low information	9.1217**	-0.3515
commitment	-21.9127***	-2.0017***
search cost	-27.1746***	1.0813*
large market	35.9436***	2.7205***
# offers	-	0.1922***
constant	37.0076***	2.6655***
obs.	378	378
(pseudo) R^2	0.7468	0.8047

Table 5: The effect of the treatment variables the number of offers (regression 1) and number of acceptances (regression 2) in each market. OLS regression analysis results. Significant coefficient estimates at ***1%, **5%, *10%. Standard errors clustered at market level.

The first numerical column of Table 5, which refers to the average number of offers per subject, shows that every variable is statistically significant in explaining offers. A large market size increases the average number of offers. Having less information on others' preferences is associated

[20] Period is an integer from 1 to 15 in the small markets, and 1 to 9 in the large ones. Since we essentially repeated the same games several times (given that there are no relevant differences across different preference profiles), period appears in the regressions to control for some learning that appears due to the "usual" static repetition of the games.

with a higher number of offers on average, even though the magnitude of this effect is smaller. On the other hand, both frictions—commitment and costly search—significantly reduce the average number of offers per subject. It therefore follows that, Hypothesis 1 cannot be rejected.[21]

For a deeper analysis of how the number of offers is affected, consider the OLS regression results in regression 3 in Table 6 when cross-effects among the treatment variables are allowed.

Market activity				Offers reg. 3	Acceptances reg. 4
period				-0.9651***	0.1119***
low	com	cst	$\boxed{\text{lrg}}$	49.4380***	4.8101**
low	com	$\boxed{\text{cst}}$	lrg	-11.6667***	1.0082**
low	com	$\boxed{\text{cst}}$	$\boxed{\text{lrg}}$	3.1602***	5.1309***
low	$\boxed{\text{com}}$	cst	lrg	-7.0222***	-0.5550**
low	$\boxed{\text{com}}$	cst	$\boxed{\text{lrg}}$	11.3269***	0.4762
$\boxed{\text{low}}$	com	cst	lrg	8.7556***	0.3816
$\boxed{\text{low}}$	com	cst	$\boxed{\text{lrg}}$	86.6047***	1.3354
$\boxed{\text{low}}$	com	$\boxed{\text{cst}}$	lrg	-8.8889***	1.2676***
$\boxed{\text{low}}$	com	$\boxed{\text{cst}}$	$\boxed{\text{lrg}}$	15.9380***	5.8198***
$\boxed{\text{low}}$	$\boxed{\text{com}}$	cst	lrg	-5.6000***	-0.8654***
$\boxed{\text{low}}$	$\boxed{\text{com}}$	cst	$\boxed{\text{lrg}}$	24.7714***	-2.2478**
# offers				-	0.2026***
constant				29.2764***	1.7156*
obs.				378	378
(pseudo) R^2				0.9088	0.8325

Table 6: The effect of the treatment variables on the average number of offers (regression 3) and on the average number of acceptances (regression 4) with cross-effects. OLS regression analysis results. Significant coefficient estimates at ***1%, **5%, *10%. Standard errors clustered at market level.

The coefficient estimates from regression 3 confirm that the negative impact of cost on the average number of offers is stronger than that of commitment. The magnitude of this difference is increased when information is low or/and when markets are large. In fact, whereas the difference between the expected number of offers with commitment and cost is below 5 offers in small markets under complete information, it reaches 28 offers in large markets with incomplete information. On the other hand, low information levels increase the average number of offers in almost all cases, particularly when combined with a large market size, with the only exception being the combination of low information and costly search. We summarize the effect of treatment variables on the average number of offers as follows.

Result 1. *The average number of offers is significantly higher when information is incomplete and when the market is large. The average number of offers is significantly lower when cost and commitment are introduced. The negative impact of cost is more important than that of*

[21] We have repeated the presented regression analysis after correcting the dependent variable for the number of participants in the market. All the reported effects keep their sign and statistical significance, except for market size in regression 2 (it loses all its explanatory power).

commitment, particularly when information is low or/and markets are large. Finally, experience slightly reduces the average number of offers on the market.

When the average number of acceptances (which corresponds to the number of deals) is concerned, consider the last columns of Table 5 and of Table 6. Regression 2, which controls for the number of offers made, describes acceptance behavior and reveals some interesting aspects. As one might expect, the size of the market and the number of offers have a positive impact on the number of acceptances. However, contrary to its influence on offering behavior, experience also seems to increase the number of acceptances. Moreover, while commitment has the negative impact predicted in Hypothesis 2, cost actually increases the number of acceptances. The reason behind this may be that there is an obvious opportunity cost to issuing a proposal when search is costly, so that costly offers create more deliberate offers, which are in general considered acceptable by the recipients, while with commitment each subject can accept at most one proposal by construction. Combined with Result 1, this observation suggests that search costs are mainly responsible for the reduction in the number of proposals, it is mainly commitment that hinders acceptance. Finally, with a fixed number of offers, information has no statistical power in explaining acceptances, which again is not in line with Hypothesis 2.

This general comment also holds for regression 4, which highlights some combinations of our treatment variables for which acceptance behavior is affected in a remarkably different way from offering behavior. In regression 4 many coefficients are not significant. Commitment does not appear to affect the number of acceptances, unless coupled with low information levels in large markets. Still, the positive impact of cost on the average number of acceptances is confirmed, particularly when combined with low information or, most significantly, a large market size. This allows us to reject Hypothesis 2. On the other hand, as it happens in specification 2, experience slightly increases the number of acceptances, a large market size has a strong positive impact, and a low information level *per se* does not affect the number of acceptances. We summarize the impact of information and frictions on the average number of acceptances in Result 2.

Result 2. *The average number of acceptances is significantly higher when the market is large. Controlling for the number of offers, the level of information has no significant effect. Cost has a positive effect on accepting behavior, particularly when combined with low information or a large market. Commitment, when combined with low information and a large market size, significantly reduces the average number of acceptances. Finally, for a given number of offers, experience slightly increases the average number of acceptances.*

It is therefore clear that market size, the information level, and frictions affect the average number of offers and acceptances. Furthermore, the proportion of offers and acceptances that are myopically rational also varies depending on the treatment. Table 7 shows the proportions of offers, acceptances, and deals that are myopically rational. As previously mentioned, the proportion of myopically rational deals corresponds to the proportion of deals among blocking pairs. Additionally, we split myopically rational offers into offers made to a single or matched recipient, and in the latter case, with whom the sender forms or does not form a blocking pair. We do not display data in treatments S3, S6, L3, and L6 as commitment guarantees full myopic rationality.[22]

TREATMENT	S1	S2	S3	S4	S5	S6	L1	L2	L3	L4	L5	L6
	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$
	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$
	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST
	LRG	LRG	LRG	LRG	LRG	LRG	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$
MYOP. RAT. OFFERS	99%	100%	–	99%	99%	–	83%	97%	–	77%	87%	–
TO SINGLE	70%	88%	–	57%	81%	–	49%	84%	–	41%	62%	–
TO MATCHED	29%	12%	–	43%	17%	–	34%	13%	–	37%	25%	–
TO MATCHED/BLOCK.PAIR	3%	6%	–	3%	2%	–	9%	5%	–	10%	9%	–
TO MATCHED/NOT BLOCK.PAIR	26%	6%	–	40%	15%	–	25%	8%	–	26%	16%	–
MYOP. RAT. ACCEPTANCES	98%	98%	–	97%	98%	–	92%	96%	–	90%	96%	–
MYOP. RAT. DEALS	97%	98%	–	96%	97%	–	82%	94%	–	80%	89%	–

Table 7: Rates of myopically rational offers split into different receiver's classes, rates of myopically rational acceptances, and rates of myopically rational deals.

The numbers in Table 7 reveal that the levels of myopic rationality in small markets are extremely high and do not depend significantly on other treatment variables; large treatments experience slightly lower levels of myopic rationality, particularly when we focus on the no-friction treatments. Looking into how offers are split between single and matched recipients, there are several interesting points to note. Clearly, proposing to a matched subject comes at a higher risk. This risk is known and often avoided when there is full information. In fact, when holding information, subjects may compare the position they are held in their target partners' preference with their current partner and this may prevent them from proposing to a married partner. This explains why offers to matched agents with whom the sender does not form a blocking pair are more frequent under incomplete than under complete information, and less frequent when there is an explicit cost to making offers than when such a cost is absent.

To better grasp the effect of treatment variables on myopic rationality, we present three logistic regressions in Table 8 in which we regress a binary variable indicating whether an offer (regression 5) or an acceptance (regression 6) is myopically rational or not, and whether a deal corresponds to resolving a blocking pair (regression 7) on the number of rounds played and on a set of dummy

[22]The numbers in Table 7 are market averages, i.e. for each treatment, we first compute the average rate per round and per group and then compute the average for all groups and all rounds, thus obtaining an average rate for each treatment.

variables indicating the level of information, whether there is a positive cost of search, and market size.

	Offers	Acceptances	Deals
	reg. 5	reg. 6	reg. 7
period	0.8659***	1.0613**	1.0440
low information	0.6505***	0.7694	0.6987***
commitment	-	-	-
search cost	2.3980***	2.0822***	2.2014***
large market	0.0339***	0.4103***	0.2459***
constant	320.6477***	20.3664***	15.5972***
obs.	7904	2668	2668
(pseudo) R^2	0.1661	0.0482	0.0878

Table 8: The effect of the treatment variables on myopic rationality of offers (regression 5), acceptances (regression 6), and deals (regression 7). Odds ratios from logistic regressions. Significant estimates at ***1%, **5%, *10%. Standard errors clustered at subject level in regressions 5 and 6, and at market level in regression 7.

The results show that the estimated odds ratios associated with experience, low information, or with a large market size are significant and below 1, and the estimated effect associated with the latter is much smaller than the effect of the other two. On the other hand, the existence of search costs increases the proportion of myopically rational offers, so that when sending an offer is costly, subjects tend to strategize less. Even though the latter result is consistent with Hypothesis 3, the fact that low information and a large market size reduce rationality indicates that we should reject this hypothesis. Nevertheless, when we account for cross-effects among the treatment variables, as we do in regression 8 (see Table 9), the coefficient associated with low information is not statistically significant (and is above 1, indicating that low information would increase rationality of offers). The negative impact of low information can only be felt in large markets, since the coefficients associated with the cross-effects between low information and a large market (and cost) are significant and below 1. Finally, the negative impact of experience can be explained by the fact that violations of myopic rationality reflect strategizing behavior. We summarize the effect of information and frictions on myopic rationality of offers as follows.

Result 3a. *The proportion of myopically rational offers is significantly lower in large markets and when low information is combined with a large market (and with costly search). When compared to the baseline treatments, the proportion of myopically rational offers is significantly higher in the presence of cost. Finally, the proportion of myopically rational offers decreases with experience.*

We next investigate the effect of information and frictions on myopic rationality of acceptances. We again employ two logistic regressions, whose results are shown in Table 8 (regression 6) and of Table 9 (regression 9). The results indicate that low information does not have a significant

				Offers reg. 8	Acceptances reg. 9	Deals reg. 10
period				0.8668***	1.0609**	1.0442
low	com	cst	$\boxed{\text{lrg}}$	0.0454***	0.4248***	0.2163***
low	com	$\boxed{\text{cst}}$	lrg	6.3433*	2.0598	2.9248***
low	com	$\boxed{\text{cst}}$	$\boxed{\text{lrg}}$	0.2417***	0.8456	0.7557
low	$\boxed{\text{com}}$	cst	lrg	-	-	-
low	$\boxed{\text{com}}$	cst	$\boxed{\text{lrg}}$	-	-	-
$\boxed{\text{low}}$	com	cst	lrg	1.8855	0.9302	0.8653
$\boxed{\text{low}}$	com	cst	$\boxed{\text{lrg}}$	0.0326***	0.3011***	0.1744***
$\boxed{\text{low}}$	com	$\boxed{\text{cst}}$	lrg	0.7723	1.1626	0.8555
$\boxed{\text{low}}$	com	$\boxed{\text{cst}}$	$\boxed{\text{lrg}}$	0.0659***	0.8102	0.3683***
$\boxed{\text{low}}$	$\boxed{\text{com}}$	cst	lrg	-	-	-
$\boxed{\text{low}}$	$\boxed{\text{com}}$	cst	$\boxed{\text{lrg}}$	-	-	-
constant				219.9784***	20.0575***	15.7285***
obs.				7904	2668	2668
(pseudo) R^2				0.1722	0.0500	0.0923

Table 9: The effect of the treatment variables on myopic rationality of offers (regression 8), acceptances (regression 9), and deals (regression 10) considering cross-effects. Odds ratios from logistic regressions. Significant estimates at ***1%, **5%, *10%. Standard errors clustered at subject level in regressions 8 and 9, and at market level in regression 10.

effect on the rationality of acceptances, unless combined with a large market size, in which case rationality is lower than in the default situation. In addition, a large market size has a significant (individual) negative impact. Contrary to what we can observe for offers, myopic rationality of acceptances appears to be enhanced, even if only slightly, by experience. Finally, it is hard to evaluate the effect of cost. Whereas its effect appears to be positive and significant in specification 6, no coefficient associated with cost or with any of its cross-effects is significant in specification 9, in line of what we could expect, given that we model search costs as the costs of sending offers.

Result 3b. *There is no significant effect of information nor of cost on the frequency of myopically rational acceptances. However, the number of myopically rational acceptances is significantly lower when the market is large and experience slightly increases the frequency of myopically rational acceptances.*

Finally, a few remarks on the proportion of myopically rational deals, i.e. the proportion of deals that correspond to blocking pairs being resolved. Table 7 shows that the rationality of deals is quite high, as it exceeds 80% in all our treatments. Large markets slightly under-perform and incomplete information also seems to be detrimental, while cost increases the myopic rationality of deals. Regression 7 in Table 8 and regression 10 in Table 9 offer a clearer and statistically more accurate view on how the interactions between offers and acceptances in producing rational deals is affected by our treatment variables. Regression 7 suggests that the rationality of deals follows the patterns of the rationality of offers, in line with what numbers in Table 7 show. The nuance that regression 10 adds to this picture is that the effect of market size dominates all the other reported effects. The only way to guarantee the myopic rationality of deals in large markets is to impose commitment. It follows that our data allow us to reject Hypothesis 3.

Result 3c. *The proportion of deals that correspond to satisfying blocking pairs is significantly lower in large markets and when low information is combined with a large market (and with costly search). When compared to the baseline treatments, the proportion of deals that correspond to satisfying blocking pairs is significantly higher in the presence of cost.*

Before moving on to the analysis of stability and efficiency of the final outcome, we have a last look at the dynamics that led to such outcomes. Overall, Figure 1 presents the evolution of the average number of blocking pairs over the duration of a round in each treatment (blue circles), as well as the evolution of average aggregate payoffs (red triangles). The figure suggests that blocking pairs tend to disappear over time in all treatments, even though the pace at which they vanish depends on the treatment. In treatments without frictions, there is an abrupt reduction in the number of blocking pairs in the first seconds. In fact, in these treatments, when 20% of a round had elapsed, small and large markets had on average roughly 5 and 20 blocking pairs, respectively, which corresponds to 20% of the maximum number of blocking pairs in these markets. However, this drop is less pronounced in the second half of each round, where it seems that some agents experiment a bit and the number of blocking pairs varies.

In treatments with a positive cost for making offers, the initial decrease in the number of blocking pairs is less pronounced (which can in part be due to the fact that market activity is significantly reduced) and, moreover, in the second half of the round the number of blocking pairs exhibits a somewhat erratic behavior, particularly in the small markets. Finally, in treatments with commitment the reduction in the number of blocking pairs occurs at an extremely fast and approximately constant pace.[23] In fact and somewhat surprisingly, these are the treatments that exhibit the best performance.

As a final remark, we observe that average payoffs tend to evolve in the opposite direction, increasing as time passes and the number of blocking pairs is reduced. This is the case in treatments with commitment, but it is not so evident in some treatments where search is costly.

5.2 Stability

We now turn our attention to the proportion of stable matchings. For our purposes, a matching is stable if and only if it has no blocking pairs, i.e. pairs of agents who are not matched to each other,

[23] Note that in the treatments with commitment we count the total number of blocking pairs, even those involving agents that match and are therefore incapable of making or receiving new offers.

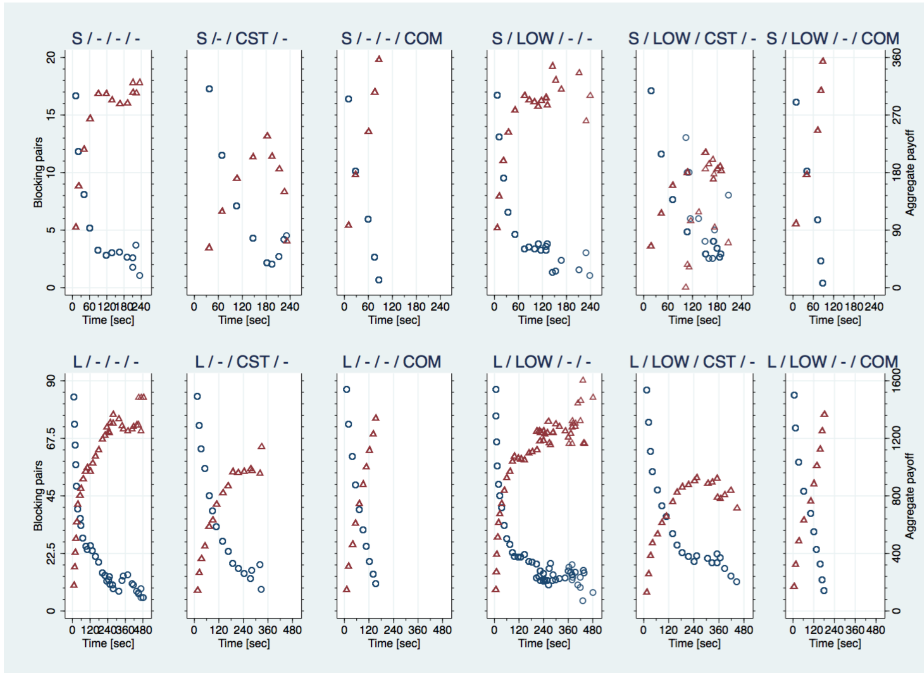

Figure 1: The evolution of the number of blocking pairs and average payoffs. Blocking pairs in blue circles, aggregate payoffs in red triangles.

but would prefer to be so matched. Table 10 contains the percentage of final matchings that are stable, as well as the average number of blocking pairs to the final matching.

Based on the previously discussed theoretical results (namely Roth and Vande Vate [25]), if agents can interact freely in a decentralized market, as in our baseline treatments, every outcome matching is expected to be stable. Nevertheless, our experimental results indicate that this is not the case. In the no-friction, low information treatments the percentage of stable matchings is 82% when the market is small and reaches a disappointing percentage of 6% when the market is large, whereas in the corresponding high information treatments, the corresponding percentages are 69% and 28%, respectively.

TREATMENT	S1	S2	S3	S4	S5	S6	L1	L2	L3	L4	L5	L6
	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$
	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$
	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST
	LRG	LRG	LRG	LRG	LRG	LRG	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$
STABLE	69%	58%	53%	82%	31%	71%	28%	28%	17%	6%	0%	22%
BLOCKING PAIRS (FINAL MATCHING)	0.80	1.40	0.64	0.33	1.44	0.40	8.72	7.61	10.50	7.50	10.50	7.83

Table 10: Percentage of games that end with a stable matching and the average total number of blocking pairs to the final matching.

Moreover, cost never improves stability (when we compare a cost treatment with the corresponding baseline treatment). On the contrary, cost severely affects stability, particularly under low information. One possible explanation for this 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 (see Result 1). However, commitment is less detrimental in general and has a positive impact under low information when the market is large. Finally, the numbers in Table 10 do not allow us to draw any conclusion regarding the impact of information on stability.

				STABILITY	
				REG. 11	REG. 12
PERIOD				1.1694***	1.1338***
LOW INFORMATION				0.8420	–
COMMITMENT				0.6258	–
SEARCH COST				0.2929***	–
LARGE MARKET				0.1684***	–
LOW	COM	CST	$\boxed{\text{LRG}}$	–	0.2507***
LOW	COM	$\boxed{\text{CST}}$	LRG	–	0.5836
LOW	COM	$\boxed{\text{CST}}$	$\boxed{\text{LRG}}$	–	0.2507***
LOW	$\boxed{\text{COM}}$	CST	LRG	–	0.4764*
LOW	$\boxed{\text{COM}}$	CST	$\boxed{\text{LRG}}$	–	0.1277**
$\boxed{\text{LOW}}$	COM	CST	LRG	–	2.2349*
$\boxed{\text{LOW}}$	COM	CST	$\boxed{\text{LRG}}$	–	0.0368***
$\boxed{\text{LOW}}$	COM	$\boxed{\text{CST}}$	LRG	–	0.1678***
$\boxed{\text{LOW}}$	COM	$\boxed{\text{CST}}$	$\boxed{\text{LRG}}$	–	(0!)
$\boxed{\text{LOW}}$	$\boxed{\text{COM}}$	CST	LRG	–	1.224
$\boxed{\text{LOW}}$	$\boxed{\text{COM}}$	CST	$\boxed{\text{LRG}}$	–	0.1843***
CONSTANT				0.9098	0.6333
OBS.				378	360
(PSEUDO) R^2				0.2080	0.2239

Table 11: The effect of the treatment variables on stability of the final matching without (regression 11) and with (regression 12) cross-effects. Odds ratios from logistic regressions. Significant estimates at ***1%, **5%, *10%. Standard errors clustered at market level. (0!) Category predicts failure perfectly.

An alternative measure for the stability of the outcome is the number of existing blocking pairs to the final matching. The last row in Table 10 presents the average numbers for each treatment and supports our observations discussed above, even if the two measures do not agree fully on the stability ranking of our treatments.[24]

In order to better evaluate the impact of treatment conditions on stability, consider the two logistic regressions presented in Table 11. The dependent variable is a binary variable indicating whether the outcome matching is stable or not. In specification 11, the independent variables are

[24]The apparent discrepancies are probably due to statistically insignificant differences between some pairs of treatments. We do not find this problematic, because when looking at averages we focus on size effects and postpone the discussion on statistical significance to the regression analysis.

the number of rounds played and a set of dummy variables indicating the level of information, whether there is a positive cost of search, and market size, to which we add cross-effects in specification 12. The two regressions confirm our intuition. A low information level *per se* does not have a significant impact on the proportion of final stable matchings. However, a large market size severely affects stability. Cost also reduces stability, particularly when combined with a large market size and a low information level. As for commitment, even though it is not stability enhancing, commitment's negative effect is not statistically significant, unless when coupled with a large market size. Results on the impact of commitment and a large market size allow us to reject Hypothesis 4. We summarize our results as follows.

Result 4. *The proportion of stable matchings is significantly lower in large than in small treatments. The level of information does not significantly affect stability. Moreover, cost negatively affects the proportion of stable matchings, while the negative effect of commitment is felt only when commitment is combined with a large market size. Finally, experience slightly increases the proportion of stable matchings.*

5.3 Efficiency

As previously mentioned, the proxy we use to evaluate efficiency of experimental markets is the fraction of the highest possible sum of payoffs that is captured by subjects in an experimental session. We split the games into two categories: those that achieve average payoffs below 80% and above 80% of the maximum possible payoff. We refer to the latter as "efficient" matchings. In Table 12 we present the percentage of games that achieved average payoffs in each category.

TREATMENT	S1	S2	S3	S4	S5	S6	L1	L2	L3	L4	L5	L6
	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	LOW	LOW	LOW	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$	$\boxed{\text{LOW}}$
	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$	COM	COM	$\boxed{\text{COM}}$
	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST	CST	$\boxed{\text{CST}}$	CST
	LRG	LRG	LRG	LRG	LRG	LRG	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$
BELOW 80%	16%	73%	0%	4%	91%	0%	50%	67%	28%	22%	72%	6%
AT LEAST 80%	84%	27%	100%	96%	9%	100%	50%	33%	72%	78%	28%	94%

Table 12: Percentage of games that achieved average payoffs below and above 80% of the maximum possible payoff in each game.

Several points are of note here. First of all, a low information level is associated with higher levels of efficiency, unless low information is combined with costly offers. Moreover, and quite surprisingly, treatments with commitment correspond to the highest efficiency levels, followed by treatments without frictions, whereas costly offers present the lowest efficiency levels. In fact, costly offers have a significant negative impact on the percentage of games that achieve payoffs above 80% of the maximum achievable payoff.

For a statistical analysis of our treatment variables, we again turn to regression analysis. Table 13 shows the estimated odds ratios for two logistic regressions. In both regressions, the dependent variable is our proxy for efficiency, which takes the value of 1 if the achieved aggregate payoff is at least 80% of the highest possible level and 0 otherwise. The independent variables are the number of rounds played, the dummy variables for the level of information, frictions, and market size (regression 13), as well as cross-effects (regression 14).

				Efficiency	
				reg. 13	reg. 14
period				1.3594***	1.5826***
low information				1.1805	–
commitment				4.9384**	–
search cost				0.0196***	–
large market				0.6840	–
LOW	COM	CST	$\boxed{\text{LRG}}$	–	0.2446
LOW	COM	$\boxed{\text{CST}}$	LRG	–	0.0105***
LOW	COM	$\boxed{\text{CST}}$	$\boxed{\text{LRG}}$	–	0.0983***
LOW	$\boxed{\text{COM}}$	CST	LRG	–	(1!)
LOW	$\boxed{\text{COM}}$	CST	$\boxed{\text{LRG}}$	–	0.8500
$\boxed{\text{LOW}}$	COM	CST	LRG	–	5.3490
$\boxed{\text{LOW}}$	COM	CST	$\boxed{\text{LRG}}$	–	1.2274
$\boxed{\text{LOW}}$	COM	$\boxed{\text{CST}}$	LRG	–	0.0017***
$\boxed{\text{LOW}}$	COM	$\boxed{\text{CST}}$	$\boxed{\text{LRG}}$	–	0.0319***
$\boxed{\text{LOW}}$	$\boxed{\text{COM}}$	CST	LRG	–	(1!)
$\boxed{\text{LOW}}$	$\boxed{\text{COM}}$	CST	$\boxed{\text{LRG}}$	–	7.2796*
constant				0.8923	0.4118
obs.				378	288
(pseudo) R^2				0.5124	0.5298

Table 13: The effect of the treatment variables on efficiency of the final matching without (regression 13) and with (regression 14) cross-effects. Odds ratios from logistic regressions. Significant coefficient estimates at ***1%, **5%, *10%. Standard errors clustered at market level. (1!) Category predicts success perfectly.

The odds ratios estimated for the independent variable "period" are significant and above 1, so that experience is efficiency-enhancing. The effect of a large market size is less clear, but it never increases efficiency in a statistically significant way. Low information alone does not seem to have a significant impact on efficiency but when combined with cost its effect is highly detrimental. These facts do not allow us to reject Hypothesis 5. Confirming our conclusions from the observation of Table 12, all coefficients associated with cost and its cross-effects are significant and well below 1, so that cost has an important negative impact on efficiency, whereas all significant coefficients associated with commitment are well above 1.

Result 5. *The proportion of efficient outcomes does not significantly depend on market size. Low information does not impact efficiency significantly, unless combined with search costs. More-*

over, cost significantly decreases, while commitment increases the proportion of efficient outcomes. Finally, experience slightly increases efficiency.

6 Conclusion

Most decentralized matching markets have evolved freely to exhibit a variety of features. Those features have appeared without the intervention of market designers, and they have remained unnoticed to theorists. The pervasiveness and the large variety of decentralized matching markets compel their careful study, and this paper is one step in that direction.

We have reported results from experiments on a series of markets differing in size, the level of information agents have about 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 by issuing proposals. In fact, as our experiments show, proposing behavior—reflected in the number and pace of offers made and in the identity of the receiver—heavily depends on market features. Since behavior is determinant in shaping the outcome, the obtained matching is also responsive to the environment. Costly offers have a negative impact on both stability and efficiency of the final matching, but surprisingly commitment enhances efficiency considerably, while reducing stability only in some instances (i.e., treatments). On the other hand, low information of others' preferences does not affect stability or efficiency, although it boosts market activity.

This leads us to a final remark on the grounds of mechanism design concerning the importance of frictions. While the lack of information on others' preferences by itself does not have to be a concern, as our results suggest, policy makers and matching theorists should be concerned by the presence of market frictions, particularly search costs, which appear to affect desirable properties of the market outcome. For instance, the combination of low information levels and costly search is particularly detrimental to stability and efficiency. Therefore, the benefits of introducing a centralized clearinghouse in markets that exhibit these features are potentially high.

6.1 Final remarks on Echenique and Yariv [8]

We have designed and conducted our experiments in parallel to and unaware of Echenique and Yariv [8]. While both Echenique and Yariv [8] and this paper explore decentralized markets using the experimental method and therefore share some common elements, comparison between the two sets of results is not straightforward. This short section highlights the similarities and the main differences in the experimental designs in order to explain how the two papers complement each other.

Our paper is devoted to analysing the effect of frictions and information level in decentralized markets, whereas Echenique and Yariv [8] mainly explore stability in these markets always assuming complete information and in the absence of frictions. Their markets are composed of 8 subjects on each side, although they run robustness tests to check the effects of market size, of the matching protocol (including treatments where only one side of the market is allowed to propose), and of different magnitudes of experimental incentives (the difference in utility between matching a subject's kth and $k+1$th choice is either 20¢ or 70¢). Nevertheless, the principal features of their experimental design, the rules governing participants' interaction during the experiments, were essentially the same as ours.

The main pattern that arises from Echenique and Yariv [8]'s experimental data is that the proportion of observed stable matchings decreases as the number of stable matching partners increases. In markets where agents have one, two, or three stable matching partners, a total of 90%, 89%, and 47% of the observed final matchings were stable, respectively. The average stability level is 76%. The latter number compares with an average stability level of 69% obtained in our benchmark treatment S1, which is a weighted average of the stability level of 80% obtained in market S-B where an agent has 2.2 stable matching partners on average and the stability level of 63% obtained in markets S-A and S-C where each agent has 1.4 stable matching partners on average. While Echenique and Yariv [8] claim that results do not change as market size grows to 15 agents, the reported global average stability of 67% for markets where agents have one, two, or three stable matching partners is considerably less than same global average of 76% for smaller markets. Our data reveal a larger decrease in a similar comparison: stability roughly halves as market size doubles (from 5 to 10).

As for the selection problem when more than one theoretically stable matching exists, Echenique and Yariv [8] report that "in none of [the] baseline treatments were the extreme stable matchings selected." This is rather surprising because their experimental design is based on a relatively low number of stable matchings. In our experiments, we did find a relatively large number of extreme (i.e., letter- or number-optimal) final matchings: 52% in S1 and 61% in L1 of all the observed stable matchings.[25]

Overall, the two papers deliver similar messages concerning markets with complete information and without frictions. They constitute the first experimental studies aimed at understanding decentralized matching markets and testing the available theoretical results. They also share the spirit of looking beyond and complementing the existing theoretical framework.

[25]Echenique and Yariv [8] report important differences between treatments with different monetary incentives. Although this is an important issue for the experimental method in general (e.g., Camerer [5], Read [22], Smith and Walker [26]), our treatments are not designed to explore the effect of different sizes of monetary incentives. Our design is comparable to the 20¢-treatment in Echenique and Yariv [8], given that we normalized the difference between any given partner and the next best to 10 EMU ($10/35 \approx 0.29$) in all our treatments.

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A Instructions (translated from Spanish)

The objective of this experiment is to study how people make decisions in certain situations.[26] Should you have a question, you can pose it at any moment by first 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.

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.

[26] 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 from the authors.

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.

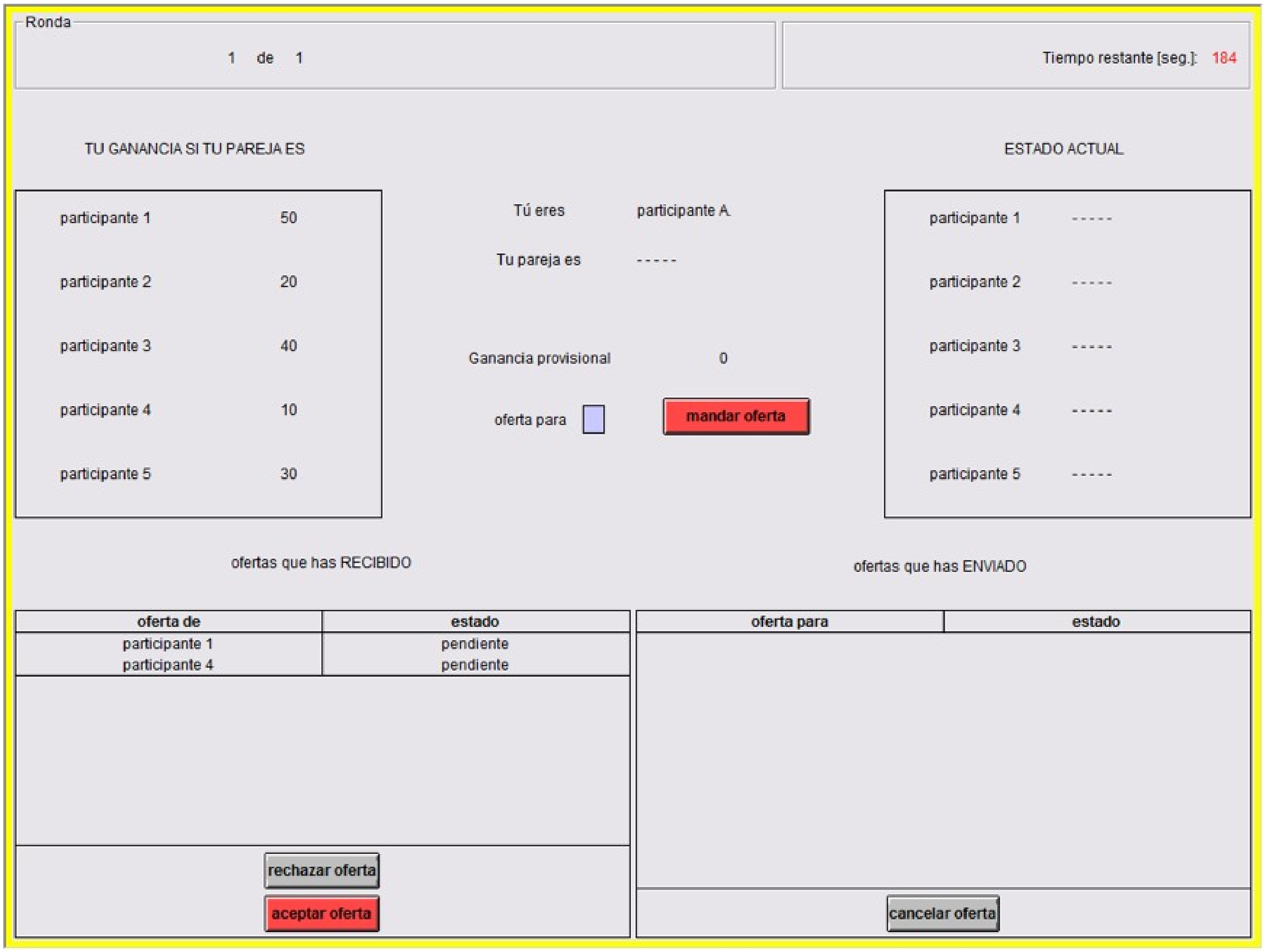
- Do not send, and do not accept any offer. This way you will remain alone, since each round starts with all participants being alone.
- You already have a partner, but she decides to leave you and to form a new partnership with somebody else from your group (or to stay alone).
- You already have a partner, 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 2: 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