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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' behavior 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 does not affect the stability or the efficiency of the final outcome, although it boosts market activity, unless coupled with search costs. Search costs have a significant negative impact on stability and on market activity. 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 Classification 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 than 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 (1990) 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 matches may not only occur among blocking pairs. Moreover, the level of information agents have 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

[1] In fully centralized two-sided matching markets, the matchmaker produces a matching of the two sides of the market using lists of preferences regarding the other side of the market that each agent submits. 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. 2005) and in the two-sided matching literature (Kagel and Roth 2000; Niederle and Roth 2009).

resolve. It is sometimes the case that the convergence process for some reason stops too early and some blocking pairs do not resolve.

Our aim in this paper is to make a step forward in answering these questions by 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 fixed 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. Where the features of the outcome are concerned, stable final 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. Surprisingly, and despite harming stability in some instances, commitment appears to boost efficiency. The treatments with commitment deliver the final matchings with the highest aggregate payoffs. Costly proposals and low information do not prevent markets from moving toward payoff-maximizing matchings. The effect of a large market size is less clear, but it never affects efficiency negatively.

Our data suggest that decentralized interaction makes blocking pairs gradually disappear over time in all treatments, even though the pace at which they vanish depends on the treatment. The main driving force behind the aggregate results is individual myopic rationality, i.e. proposals and acceptance decisions that improve upon the status quo. The intensity of market activity and the varying strength of this

[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 (2009).

[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 algorithm—a protocol that is 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.

force together offer an explanation to the observed changes in stability and efficiency of the market outcome across treatments. For instance, we find that low information by itself does not seem to drive markets away from stability or efficiency. One possible explanation for this is that increased market activity is used to gather the missing information. Nevertheless, when low information is combined with costly proposals, which seriously hinders the number of proposals, stability is severely affected. In fact, this friction affects not just the number of proposals, 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 Sect. 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 Sect. 3. In Sect. 4 we lay out our hypotheses concerning subjects' behavior and the matching outcome. Section 5 summarizes the main results of the experiments. Some concluding remarks follow in Sect. 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 (1962) have shown that a stable matching exists for every matching market by means of the Gale–Shapley algorithm (henceforth the GS algorithm), which we describe as follows. Starting from a situation in which all agents are unmatched and given a profile of preferences, every agent on 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 agent'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 on 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 successful real-life applications, the GS algorithm is used (see Roth 1991). 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 (1976) and Roth and Vande Vate (1990) have shown 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. Nevertheless, 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 (2013) have shown that some stable matchings are more likely than others.

Another question is the speed of convergence. Ackerman et al. (2008) have looked into how fast the random better-response algorithm converges to a stable matching and have shown 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, simulations have proven that the degree of correlation and intercorrelation of preferences affects the speed of convergence. Celik and Knoblauch (2007) have concluded that in markets where agents on one side rank agents on the other side in a similar way, convergence is faster than when

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

[6] The latter class was later expanded in Hoffman et al. (2013).

this is not the case. This behavior is also present in markets where participants prefer participants that prefer them (Boudreau and Knoblauch 2010).[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 (2008) has described a sequential game where, at each point in time, one agent is able to make a matching proposal and characterizes equilibrium outcomes, relating them to the concept of stability. Also Haeringer and Wooders (2011) and Diamantoudi et al. (2015) have explored sequential matching games and shown that introducing commitment may have a negative impact on the stability of matchings obtained in equilibrium. Finally, the role of transaction costs (modeled through discounting) and information has been analyzed by Niederle and Yariv (2009), where costly search combined with low information reduces the chances of obtaining a stable matching in equilibrium.

There also exists a short list of experimental papers on decentralized matching markets, most of which are rather unrelated to this paper. Comola and Fafchamps (2018), Eriksson and Strimling (2009) and Molis and Veszteg (2010) have approached one-sided matching markets. Comola and Fafchamps (2018) has been mainly concerned with analyzing behavior in a many-to-many decentralized market. They have implemented an intuitive protocol that follows the lines of Gale–Shapley algorithm and explore the role of information on others' preferences. Their results suggest that subjects reach a stable matching in the majority of cases. Moreover, a low information level decreases the speed of convergence, but, similarly to our paper, does not compromise stability, since subjects overcome their lack of information with proposals and counter-proposals. Observed behavior is consistent with reluctance to match with players who have been disloyal by rejecting previous proposals. As in our paper, this partly explains the existence of myopically-irrational behavior.

In what two-sided markets are concerned, Haruvy and Ünver (2007) have explored decentralized matching, but imposing a structure on the functioning of the market that is more rigid than ours. Only one side of the market was allowed to make proposals, one per period, and markets were repeated for a certain number of periods. They have shown that a stable matching, the one that is optimal for the proposing side of the market, is reached in the majority of cases, independently of the level of information held by subjects. Kagel and Roth (2000) have studied the transition from a decentralized market where unraveling of transactions occurs to a centralized market. Nalbantian and Schotter (1995) have looked at decentralized matching procedures when agents' payoffs constitute private information. Niederle and Roth (2009) have considered an incomplete-information setting in which one side of the market makes proposals to the other side over three experimental periods. They have studied the effects of the proposal structure—whether proposals can or cannot be put on hold—on the information that gets used in the final matching and on the resulting market efficiency.

[7] See also Boudreau (2008).

Echenique and Yariv (2013) is the closest paper to ours. They have analyzed data from experiments aimed at testing whether two-sided matching markets, where all agents can make and receive proposals in an unconstrained way, reach stable matchings and, in case more than one stable matching exists, which stable matching is reached. The principal features of their experimental design, the rules governing participants' interaction during the experiments are essentially the same as ours. Nevertheless, contrary to our paper, information is complete in those experiments and there are no market frictions: making matching proposals is costless and matching is not binding. The main pattern that arises from the experimental data gathered by Echenique and Yariv (2013) 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 are stable, respectively. The observed average stability level is 76%. As for the selection problem when more than one theoretically stable matching exists, Echenique and Yariv (2013) have reported that the extreme stable matchings are never selected in the baseline treatments and, 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. Moreover, they have run robustness tests of the matching protocol (including treatments where only one side of the market is allowed to propose) and of different magnitudes of experimental incentives.[8] They have found that the selection result is not affected when only one side of the market proposes, but the cardinal representation of agents' preferences does affect the final matching.

Overall, Echenique and Yariv (2013) and our paper 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.

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 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 proposal has a fixed cost that subjects pay from their initially

[8] The difference in utility between being matched to a subject's kth and $k+1$th choice is either 20¢ or 70¢. Our design is comparable to the 20¢-treatment in Echenique and Yariv (2013), 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.

allocated budget.[9] In all the other treatments proposals are costless, so that there is no need to give subjects an initial budget. On the other hand, in treatments with commitment, acceptance is binding, so that couples are forced to leave the market once matched. In no-friction treatments, issuing proposals is costless and there is no commitment, so that matched agents stay in the market, continue sending and receiving proposals, and eventually re-match, leaving the abandoned partner alone.

Where information on 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 markets have ten subjects—five on each side, represented by numbers from 1 to 5 and by letters from *a* to *e*—whereas large markets 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 $3 \times 2 \times 2$ design: (no-friction, costly proposals, commitment) $\times$ (low information, high information) $\times$ (small market, large market). In what follows, we usually take the no-friction, high information, small market treatment as the benchmark or baseline treatment.

In each treatment, participants play 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, preference profiles 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 under preference profiles 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 under preference profiles L-A, L-B and L-C, respectively.

Tables 1 and 2 in Supplementary material contain the preference profiles and a summary of their features. Note that preference profiles in large markets have some resemblance to preference profiles in small markets. Namely, a market with preference profile L-A consists of two embedded markets with preference profiles

[9] The per-proposal cost was 4 Experimental Monetary Units (EMU) with an initial budget of 16 EMU. The part of the budget that was not spent on sending proposals was added to the subjects' final payoff in each round. Given our objective to analyze the effect of market frictions on market outcome, we chose the amount of the per-proposal cost and the initial budget as to introduce significant search costs in the corresponding treatments, without them being too restrictive. In order to illustrate the impact of search costs, we have simulated 10 thousand markets for each of our six preferences profiles. Simulated interaction happened through random encounters between myopically-rational agents who would never repeat partners who had rejected or abandoned them before. We find that the shortest paths towards a stable matching is of 6 to 13 interactions long in small markets, and it is of 18 to 53 interactions in large markets.

[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.

identical to S-A—one market composed of agents 1 to 5 and *a* to *e* and the other composed of agents 6 to 10 and *f* to *j*—so that in any stable matching of the market with preference profile L-A, each agent is matched to someone who belongs to the same market-component. The same relation holds between markets with preference profiles L-B and S-B, and between markets with preference profiles L-C and S-C.

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 2007).[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 Supplementary material.

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 preference profile S-A, S-B and S-C five times in a row (fifteen paying rounds in total), whereas in large treatments subjects played preference profiles 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).

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 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 proposals on the screen. At any time throughout the game a subject could issue proposals to any participant on the other side of the market, i.e. in the other set of the same group, or respond to proposals received. However, a participant could only make one proposal at a time. This means that in no-commitment treatments a participant could not send a new proposal until the previous one had been either accepted or rejected by the other participant, or withdrawn by the sender. In commitment treatments, since acceptance resulted in the matched couple leaving the market, a participant could only send a new proposal once the previous one had been rejected or withdrawn.

The status of a proposal 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 a proposal to themselves and accept it freely in order to become single again at any moment in time (provided they did not have

[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.

any pending sent proposal). Finally, in order to keep the amount of real-time information on screen manageable (and because it resembles reality more), a participant would only receive information on the status of the proposals that she had made and received, and on the current matching in her market.

In small-market treatments, each round had a fixed duration of 4.5 minutes, whereas in large-market 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-market 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-market 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-market and the large-market treatments, including a show-up fee.[14]

Table 1 below contains a summary of all treatments. In total, six out of twelve sessions correspond to small-market treatments (treatments S1 to S6), combining a high or low information level with the no-friction, costly proposals, and commitment scenarios. The remaining six sessions correspond to large-market treatments, with the same combinations of information level and frictions (treatments L1 to L6).

[12] The addition of this flexible ending rule in the large-market 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. Time limits are unavoidable design elements of any laboratory experiment. Echenique and Yariv (2013) do not set an exogenous limit for the duration of a round, instead they force each market to end after 30 s of inactivity. And, when receiving a proposal, subjects have at most 10 s to respond. Comola and Fafchamps (2018) opt for a design in which subjects take turns to make proposals. In this case, even though there are no explicit time limits, other constraints are in place. Namely, each subject has a maximum number of turns to propose (8), in each turn each subject can make a limited number of proposals (5), and each subject has at most 15 s to make a decision (either to propose or to react to a received proposal). Similar restrictions were introduced by Echenique et al. (2016) who consider a dynamic version of the deferred-acceptance algorithm. In their setup, subjects are simply not allowed to repeat proposals; additionally, proposers have 30 s to make a proposal and respondents have 25 s to react.

The computer simulations mentioned earlier show that, on average, our markets take 19 proposals to settle when they are small and 75 proposals when they are large. The outcome is a stable matching in 99.8% of the cases in small markets and in 96.8% of the cases in large markets. If proposals take 5 s to be made and 5 s to be considered, overall stability is very high: it is equal to 99.8% in small markets and 83.5% in large markets given the above time limits. The proportion, however, drops dramatically to 86% in small markets and to 11.4% in large markets when the time required for each decision doubles to 10 s.

[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] A conveniently adjusted conversion rule from EMU to euro made sure that subjects earned the same amount of money on average in small-market and in large-market treatments. In small-market treatments subjects received 1€ per 35 EMU, whereas in large-market treatments subjects received 1€ per 40 EMU.

Table 1 Treatment summary

	All treatments					
Market activity	both sides propose					
Timing	real-time action					
Number of proposals	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		
Number of subjects per session	30			40		
	S1/S4	S2/S5	S3/S6	L1/L4	L2/L5	L3/L6
Friction	no	costly proposals	commitment	no	costly proposals	commitment
Information	high/low	high/low	high/low	high/low	high/low	high/low

4 Hypotheses

In this section, based on intuition and the few existing theoretical results, we formulate our hypotheses concerning how the levels of stability and efficiency of the final outcome depend on market features.

Roth and Vande Vate (1990) 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 a stable matching is obtained with probability one when all blocking pairs have positive probability of resolving. This implies that in frictionless markets we may expect agents who act straightforwardly, according to their true preferences, and exhaust all opportunities to reach a stable matching. Acting straightforwardly means sending out *myopically-rational proposals*, i.e. making proposals to agents that are better than one's current partner, as well as carrying out *myopically-rational acceptances*, i.e. only accepting proposals from agents that are ranked better than one's current partner, thus improving upon the status quo. Clearly, a blocking pair is satisfied when a myopically-rational proposal is responded with a myopically-rational acceptance.

In markets with commitment, every agent in the market starts unmatched, and leaves the market upon acceptance. Since agents find each potential partner acceptable, in these treatments, by design, all proposals and acceptances are myopically-rational and all pairs that form are blocking pairs to the previous matching. Nevertheless, in the other decentralized markets that we test, agents may violate straightforward play and act according to some sophisticated, farsighted strategies. Whether or not agents actually do so may depend on market features.

In fact, market features may also affect the level of market activity, the timing of proposals and acceptances, and the identity of the agents involved. Therefore, they may have an effect on myopically-rational behavior and thus on the proportion of deals that correspond to satisfying blocking pairs. For example, a positive cost for sending out proposals may enhance myopic rationality with respect to the no-friction case, since strategizing may come at a higher cost and agents may be inclined to think their proposals better through, while such costs have no predictable impact on myopically-rational acceptance. Eventually, this type of search costs may lead to a higher proportion of deals among blocking partners.

Given that in treatments with incomplete information a priori there is hardly any information to strategize on and it is hard to imagine that proposals and acceptance decisions are actually motivated by farsighted behavior, it may be the case that the proportion of myopically-rational proposals and acceptances per subject, and thus the proportion of satisfied blocking pairs, are higher when information is incomplete.

As for market size, a large market 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. Since there is no reason to believe that these influences are actually significant, we summarize this discussion in Hypothesis 1 as follows.

Hypothesis 1 *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 search costs.*

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. Even if all agents send out and accept proposals in a myopically-rational way, they may reject proposals from or refrain from sending out all proposals 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 proposals 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. Theoretical results presented by Haeringer and Wooders (2011), and Diamantoudi et al. (2015) support this hypotheses according to which commitment drives the equilibrium outcome away from stability.

Where cost is concerned, Niederle and Yariv (2009) have shown that, in certain environments, the cost of searching for a partner affects stability negatively when information is low. A possible intuition for this is that under incomplete information, even if there is less information to strategize on, the path to stability may be harder to find since blocking possibilities are harder to spot. In this case, search costs are particularly detrimental for their predictable impact on market activity. In fact, when search costs exist, we expect the decision of issuing a proposals to be less automatic and more carefully considered than in baseline treatments. With reduced market activity, less information is conveyed and eventually some blocking opportunities remain undiscovered.

In what the remaining market features are concerned, 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 hypotheses.

Hypothesis 2 *In 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 two-sided matching markets, 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 individual payoffs as a percentage of the maximum achievable payoff in the market. Hypothesis 2 predicts that full stability is achieved in frictionless markets, independently of the level of information and of market size. Since each stable matching in markets with preference profile S-A, S-B and S-C achieves an efficiency level of 83.3%, 89.5% and 100%, respectively, with identical percentages for large markets, we predict an average efficiency level of 90.9% for all frictionless treatments.[15] Our Hypothesis 3 on efficiency therefore follows from Hypothesis 2. No predictions with respect to the impact of cost and commitment are made since Hypotheses 2 predicts that full stability is not achieved when frictions are present and failure to meet stability does not imply that a matching is not efficient.

Hypothesis 3 *In complete-information, no-friction treatments outcomes achieve an average efficiency level of 90.9%. 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. Since we could not discover any meaningful difference in market outcomes (or behavior that leads to such outcomes) induced by the different preference profiles, for the sake of a more focused analysis on market frictions, market size, and information, we present results from the pooled database (the three preference profiles together) across experimental treatments.

We are interested in how changes in individual behavior due to changes in the environment affect the properties of the final outcome. As a first step, we briefly analyze the market dynamics that leads to the final outcomes in each treatment in Sect. 5.1. We explore stability of the final outcome in Sect. 5.2, and we devote Sect. 5.3 to efficiency.

[15] Each stable matching in a market with preference profile S-A, S-B and S-C has an aggregate payoff of 300, 340 and 410, while the largest possible aggregate payoff is 360, 380 and 410, respectively. As for large markets, each stable matching in a market with preference profile L-A, L-B and L-C corresponds to an aggregate payoff of 1200, 1360 and 1640, with a maximum of 1440, 1520 and 1640, respectively.

5.1 Market dynamics

Figure 1 presents the evolution of the average number of blocking pairs over the duration of a round in each treatment (circles), as well as the evolution of average aggregate payoffs (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 the round had elapsed, small and large markets had on average roughly 5 and 20 blocking pairs remaining, respectively, which corresponds to 20% of the maximum number of blocking pairs in these markets. However, this negative trend 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 proposals, the initial decrease in the number of blocking pairs is less pronounced and, moreover, in the second half of the round the number of blocking pairs exhibits a somewhat erratic behavior, particularly in the small markets.

The treatments with commitment are the ones that exhibit the best performance as the reduction in the number of blocking pairs occurs at an extremely fast and approximately constant pace.[16] In treatments with commitment, we also observe that average payoffs tend to evolve in the opposite direction of the number of blocking pairs, increasing as time passes and convergence to stability occurs. This is also true in no-friction treatments, but it is not so evident in some treatments with costly search where average payoffs appear to decrease even when the number of blocking pairs decreases.

5.2 Stability

We now turn our attention to the proportion of stable matchings among the final outcomes. 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, but would prefer to be so matched.

Based on the previously discussed theoretical results (namely, Roth and Vande Vate 1990), if agents can interact freely in a decentralized market, as in our baseline treatments, every outcome matching is expected to be stable when agents that exhaust all opportunities send out and accept proposals in a myopically-rational way. For that reason, as a first step in the analysis of stability, we explore the proportions of proposals, acceptances, and deals that are myopically-rational in each treatment. As previously mentioned, the proportion of myopically-rational deals corresponds to the proportion of deals among blocking pairs. We display these numbers in Table 2, where we also split myopically-rational proposals into

[16] Note that, in order to make comparisons across treatments possible, in treatments with commitment we count the total number of blocking pairs including those involving agents who are matched and therefore are incapable of making or receiving new proposals.

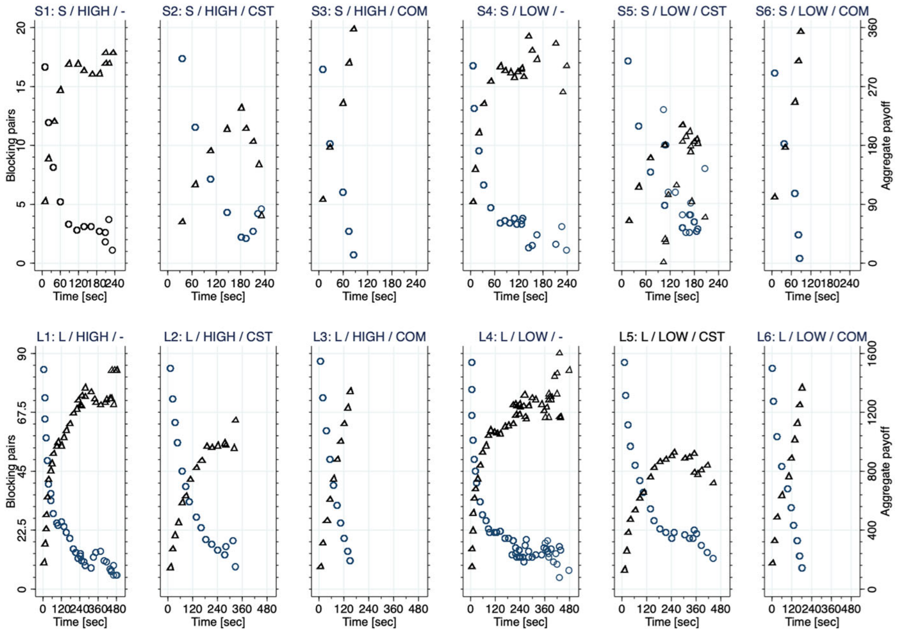

Fig. 1 The evolution of the number of blocking pairs and average payoffs (excluding search budgets and search costs). Number of blocking pairs in circles, aggregate payoffs in triangles

Table 2 Rates of myopically-rational proposals split into different receiver's classes, rates of myopically-rational acceptances, and rates of myopically-rational deals

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. proposals	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%	–

proposals 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 numbers for treatments S3, S6, L3 and L6 as commitment guarantees the myopic rationality of all decisions.[17]

The numbers in Table 2 reveal that the levels of myopic rationality in small markets are extremely high and do not depend largely on other treatment variables. Large-market treatments experience slightly lower levels of myopic rationality, particularly when we focus on the no-friction treatments. When looking into how proposals 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 enough information, subjects may compare the position they are held in their target partners' preferences with the position in the their current partner's, and this may prevent them from proposing to an already matched subject. This explains why proposals to matched subjects 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 proposals than when such a cost is absent.

To better grasp the effect of treatment variables on myopic rationality, we present estimation results for three logistic regressions in Table 3 in which we regress a binary variable indicating whether a proposal (regression 1) or an acceptance (regression 2) is myopically-rational or not, and whether a deal corresponds to resolving a blocking pair (regression 3) on the number of rounds played and on a set of dummy variables indicating the level of information, whether there is a positive cost of search, and market size.[18]

The results show that the estimated odds ratios associated with experience, low information, and with a large market size are significant and below 1, and the estimated (negative) effect associated with the latter is much larger (in absolute terms) than the effect of the other two. On the other hand, the existence of search costs increases the proportion of myopically-rational proposals, so that when sending a proposal is costly, subjects tend to strategize less. Even though the latter result is consistent with Hypothesis 1, the fact that low information and a large market size reduce myopic rationality dictates that we should reject this hypotheses.

Nevertheless, when we account for cross-effects among the treatment variables, as we do in regression 4 (see Table 4), the coefficient associated with low information is not statistically significant. The negative impact of low information is only observed in large markets, since the coefficients associated with the cross-effects between low information and a large market (and cost) are significant and the odds ratios are below 1. Finally, the negative impact of experience indicates that,

[17] The numbers in Table 2 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.

[18] Round is an integer from 1 to 15 in the small-market treatments, and 1 to 9 in the large-market ones. Given that we essentially repeated the same games for several times (and that there are no relevant differences observed across the different preference profiles), ROUND appears in the regressions to control for possible learning due to the static repetition of the games.

Table 3 The effect of the treatment variables on the myopic rationality of proposals (regression 1), acceptances (regression 2), and deals (regression 3)

	Proposals reg. 1	Acceptances reg. 2	Deals reg. 3
Round	0.8659***	1.0613	1.0440
	(0.0482)	(0.0404)	(0.0469)
Low information	0.6505***	0.7694***	0.6987**
	(0.0785)	(0.0532)	(0.0814)
Commitment	–	–	–
Search cost	2.3980***	2.0822***	2.2014***
	(0.5272)	(0.2372)	(0.3314)
Large market	0.0339***	0.4103***	0.2459***
	(0.0165)	(0.0690)	(0.0561)
Constant	320.6477***	20.3664***	15.5972***
	(221.0411)	(6.0383)	(5.6818)
Obs.	7904	2668	2668
(Pseudo) R^2	0.1661	0.0482	0.0878

Odds ratios from logistic regressions. Significant estimates at ***1%, **5%, *10%. Standard errors clustered at session level (between parentheses)

as the experimental sessions proceed, participants tend to violate straightforward behavior more often by proposing to potential partners that are ranked worse than the status quo. We summarize the effect of information and frictions on myopic rationality of proposals as follows.

Result 1a. *The proportion of myopically-rational proposals 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 proposals is significantly higher in the presence of search costs. Finally, the proportion of myopically-rational proposals decreases with experience.*

We next investigate the effect of information and frictions on myopically-rational acceptances. We again employ two logistic regressions, whose results are shown in Table 3 (regression 2) and Table 4 (regression 5). The results indicate that low information does not have a significant 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 negative impact. Contrary to what we observe for proposals, myopic rationality of acceptances appears to be enhanced, even if only slightly, by experience. Finally, it is hard to evaluate the effect of search costs. Whereas their effect appears to be positive and significant in specification 2, no coefficient associated with search costs or with any of their cross-effects is significant in specification 5. This result is in line with our expectations, given that we model search costs as the costs of sending proposals and they do not affect the receivers directly.

Result 1b. *There is no significant effect of information nor of search costs on the frequency of myopically-rational acceptances. However, the number of myopically-*

Table 4 The effect of the treatment variables on myopic rationality of proposals (regression 4), acceptances (regression 5), and deals (regression 6) considering cross-effects

	Proposals reg. 4	Acceptances reg. 5	Deals reg. 6
Round	0.8668***	1.0609**	1.0442
	(0.0191)	(0.0299)	(0.0317)
LOW COM CST $\boxed{\text{LRG}}$	0.0454***	0.4248***	0.2163***
	(0.0150)	(0.1411)	(0.0409)
LOW COM $\boxed{\text{CST}}$ LRG	6.3433*	2.0598	2.9248**
	(6.5233)	(1.1151)	(1.3252)
LOW COM $\boxed{\text{CST}}$ $\boxed{\text{LRG}}$	0.2417***	0.8456	0.7557
	(0.0973)	(0.3532)	(0.3639)
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
	(0.8657)	(0.3232)	(0.1586)
$\boxed{\text{LOW}}$ COM CST $\boxed{\text{LRG}}$	0.0326***	0.3011***	0.1744***
	(0.0107)	(0.0918)	(0.0454)
$\boxed{\text{LOW}}$ COM $\boxed{\text{CST}}$ LRG	0.7723	1.1626	0.8555
	(0.3971)	(0.4681)	(0.5541)
$\boxed{\text{LOW}}$ COM $\boxed{\text{CST}}$ $\boxed{\text{LRG}}$	0.0659***	0.8102	0.3683***
	(0.0222)	(0.3232)	(0.0780)
$\boxed{\text{LOW}}$ $\boxed{\text{COM}}$ CST LRG	–	–	–
$\boxed{\text{LOW}}$ $\boxed{\text{COM}}$ CST $\boxed{\text{LRG}}$	–	–	–
Constant	219.9784***	20.0575***	15.7285***
	(81.5478)	(6.3722)	(4.1974)
Obs.	7904	2668	2668
(Pseudo) R^2	0.1722	0.0500	0.0923

Odds ratios from logistic regressions. Significant estimates at ***1%, **5%, *10%. Standard errors clustered at subject level in regressions 4 and 5, and at preference-profile level in regression 6 (between parentheses)

rational acceptances is significantly lower when the market is large, and experience increases slightly the frequency of myopically-rational acceptances.

Finally, a few remarks are in order on the proportion of myopically-rational deals, i.e. the proportion of deals that correspond to blocking pairs being resolved. Table 2 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 search costs increase the myopic rationality of deals. Regression 3 in Table 3 and regression 6 in Table 4 offer a clearer and statistically more accurate view on how the interactions between proposals and acceptances in producing rational deals is affected by our treatment variables. Regression 3 suggests that the rationality of deals follows the patterns of the rationality of proposals and acceptances, in line with what numbers in Table 2 show. The nuance

Table 5 Proportion of markets that end with a stable matching and the average total number of blocking pairs to the final matching

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

that regression 6 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 1.

Result 1c. *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 search costs.*

In order to check the robustness of the above results, we have performed binary comparisons for all our treatment variables in terms of myopically-rational proposals, acceptances, and deals. Table 3 in Supplementary material reports the resulting p-values from two-sample z-tests of proportions (first) and Pearson's χ^2-tests for association (second). Note that none of our conclusions listed above is altered.

We now turn our attention to the proportion of stable matchings among the final outcomes. Table 5 contains the relative frequency of final matchings that are stable, as well as the average number of blocking pairs to the final matching in each treatment. Even if the percentages for myopically-rational deals are in general very high, the numbers in Table 5 reveal that the relative frequency of stable matchings varies a lot depending on the treatment. In the no-friction, high-information treatments the proportion of stable matchings is 69% when the market is small and 28% when the market is large, whereas in the corresponding low information treatments the proportions are 82% for a small market and reach a disappointing percentage of 6% when the market is large.[19]

Search costs never improve stability (when we compare a cost treatment with the corresponding baseline treatment). On the contrary, costs severely affect stability, particularly under low information. However, commitment is less detrimental in

[19] The average stability level in Echenique and Yariv (2013) of 76% compares with an average stability level of 69% obtained in our benchmark treatment S1. While Echenique and Yariv (2013) 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 the 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).

general and has a positive impact under low information when the market is large. Finally, the numbers in Table 5 do not allow us to draw any conclusion regarding the impact of information on the relative frequency of stable matchings.

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 5 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.[20]

In order to better evaluate the impact of treatment conditions on stability, consider the estimation results for two logistic regressions presented in Table 6. The dependent variable is a binary variable indicating whether the outcome matching is stable or not. In specification 7, the independent variables are 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 8. 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 low information level. As for commitment, the negative effect of commitment on stability 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 2. We summarize the results as follows.

Result 2. *The proportion of stable matchings is significantly lower in large-market than in small-market treatments. The level of information does not significantly affect stability. Moreover, search costs negatively affect the proportion of stable matchings, while the negative effect of commitment is observed only when commitment is combined with a large market size. Finally, experience slightly increases the proportion of stable matchings.*

One possible explanation for the negative impact of search costs on stability lies in the fact that costly proposals hinder market activity.[21] To start, in treatments with search costs, the initially allocated budget was enough to make 4 proposals only and several participants exhausted their budgets.[22] While it is also the case that commitment significantly reduces the average number of proposals per subject, the negative impact of search costs is stronger than that of commitment and the magnitude of this difference is increased when information is low or/and when markets are large. In fact, whereas the difference between the average number of proposals with commitment and search costs is below 5 proposals in small markets

[20] 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.

[21] Table 4 in Supplementary material contains data on market activity for each treatment: average numbers of proposals, acceptances, rejections, cancellations, and reaction rates.

[22] The average proportions of participants who went “bankrupt” are 1% in treatment S2, 4% in treatment S5, 5% in treatment L2, and 18% in treatment L5.

Table 6 The effect of the treatment variables on stability of the final matching without (regression 7) and with (regression 8) cross-effects

	Stability	
	reg. 7	reg. 8
Round	1.1694**	1.1837**
	(0.0399)	(0.0418)
Low information	0.8420	–
	(0.3172)	
Commitment	0.6258	–
	(0.2586)	
Search cost	0.2929**	–
	(0.1407)	
Large market	0.1684***	–
	(0.0725)	
LOW COM CST $\boxed{\text{LRG}}$	–	0.2507*
		(0.1873)
LOW COM $\boxed{\text{CST}}$ LRG	–	0.5836*
		(0.1852)
LOW COM $\boxed{\text{CST}}$ $\boxed{\text{LRG}}$	–	0.2507
		(0.2555)
LOW $\boxed{\text{COM}}$ CST LRG	–	0.4764*
		(0.2102)
LOW $\boxed{\text{COM}}$ CST $\boxed{\text{LRG}}$	–	0.1277***
		(0.0713)
$\boxed{\text{LOW}}$ COM CST LRG	–	2.2349***
		(0.6325)
$\boxed{\text{LOW}}$ COM CST $\boxed{\text{LRG}}$	–	0.0368***
		(0.0267)
$\boxed{\text{LOW}}$ COM $\boxed{\text{CST}}$ LRG	–	0.1678***
		(0.0617)
$\boxed{\text{LOW}}$ COM $\boxed{\text{CST}}$ $\boxed{\text{LRG}}$	–	(0!)
$\boxed{\text{LOW}}$ $\boxed{\text{COM}}$ CST LRG	–	1.1244
		(0.6480)
$\boxed{\text{LOW}}$ $\boxed{\text{COM}}$ CST $\boxed{\text{LRG}}$	–	0.1843***
		(0.1176)
Constant	0.9098	0.6333
	(0.2753)	(0.2455)
Obs.	378	360
(Pseudo) R^2	0.2080	0.2239

Odds ratios from logistic regressions. Significant estimates at ***1%, **5%, *10%. Standard errors clustered at session level in regression 7, and at preference-profile level in regression 8 (between parentheses). (0!) Category predicts failure perfectly under complete information, the difference reaches almost 10 proposals in large markets with incomplete information.[23]

The analysis of data on market activity also reveals that frictions impact reaction rates differently. In cost treatments a bigger proportion of proposals made is actually acceptable (and ends up being accepted) than in the baseline treatments, while the rejection rate falls. Introducing commitment does not significantly change acceptance rates, explicit rejection rates fall in most cases, but a huge proportion of proposals (approximately 50% in each treatment with commitment) are left without response and are automatically cancelled once the proposer leaves the market.

Finally, low information levels increase market activity in almost all cases, particularly when combined with a large market size, the only exception being the combination of low information and costly search. It appears to be the case that, by hindering market activity, search costs do not allow enough information to be transmitted, making the combination of low information with costly proposals particularly harmful.

For a final check of robustness of the above results, we turn to binary comparisons for all our treatment variables in terms of the stability of the market outcome. Table 3 in Supplementary material reports the resulting p-values from two-sample z-tests of proportions (first) and Pearson's χ^2-tests for association (second). Again, none of our conclusions is altered. Note that the tests seem to disagree on the effect of commitment on stability. This could be due to the binary, and for that reason uncontrolled, nature of these tests, and because the negative effect of commitment is observed only when commitment is combined with a large market size.

5.3 Efficiency

As previously mentioned, the proxy we use to evaluate efficiency of a market-play is the fraction of the highest possible sum of payoffs attainable in the corresponding market that is captured by subjects. To ensure comparability across treatments and with theoretical considerations, in this study the reference point for observed efficiency is the matching that generates the largest possible aggregate payoff given a preference profile. This means that in analyzing efficiency, possible search costs and unused search budgets are ignored.[24] In Table 7 we present the average

[23] See Table 5 in Supplementary material, which contains the results from ordinary-least-squares regressions taking as dependent variables the average number of proposals (regression 11) and the average number of acceptances (regression 12). The independent variables are dummies indicating the level of information, the existence of commitment or search costs, and the size of the market, all cross-effects, as well as the number of rounds played. In specification 12 we additionally include the number of proposals as a regressor, since the number of acceptances is naturally bounded by the number of proposals.

[24] The efficiency analysis ignores the direct, and obviously negative impact, of search costs on surplus in order to offer a more nuanced comparison of market outcomes across our treatments. The efficiency numbers for our search-costs treatments reflect the possible indirect impact of search costs, i.e. whether markets are less or more likely to find their way to the theoretically efficient outcome in their presence.

Table 7 Realized efficiency as the % of the maximum possible payoff in each game. Realized efficiency levels net of search costs between parentheses

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	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$	$\boxed{\text{LRG}}$
Efficiency	88%	86% (72%)	92%	90%	90% (70%)	92%	85%	87% (78%)	87%	87%	85% (72%)	89%

Table 8 The effect of the treatment variables on efficiency of the final matching without (regression 9) and with (regression 10) cross-effects

	Efficiency	
	reg. 9	reg. 10
Round	0.0156***	0.0156***
	(0.0011)	(0.0010)
Low information	0.0133*	–
	(0.0067)	
Commitment	0.0230***	–
	(0.0066)	
Search cost	− 0.0103	–
	(0.0079)	
Large market	0.0129	–
	(0.0075)	
LOW COM CST $\boxed{\text{LRG}}$	–	0.0115
		(0.0408)
LOW COM $\boxed{\text{CST}}$ LRG	–	− 0.0210
		(0.0132)
LOW COM $\boxed{\text{CST}}$ $\boxed{\text{LRG}}$	–	0.0304
		(0.0446)
LOW $\boxed{\text{COM}}$ CST LRG	–	0.0405***
		(0.0106)
LOW $\boxed{\text{COM}}$ CST $\boxed{\text{LRG}}$	–	0.0309
		(0.0394)
$\boxed{\text{LOW}}$ COM CST LRG	–	0.0200*
		(0.0113)
$\boxed{\text{LOW}}$ COM CST $\boxed{\text{LRG}}$	–	0.0363
		(0.0319)
$\boxed{\text{LOW}}$ COM $\boxed{\text{CST}}$ LRG	–	0.0160
		(0.0132)
$\boxed{\text{LOW}}$ COM $\boxed{\text{CST}}$ $\boxed{\text{LRG}}$	–	0.0076
		(0.0421)
$\boxed{\text{LOW}}$ $\boxed{\text{COM}}$ CST LRG	–	0.0318**
		(0.0155)
$\boxed{\text{LOW}}$ $\boxed{\text{COM}}$ CST $\boxed{\text{LRG}}$	–	0.0477
		(0.0356)
Constant	0.7628***	0.7592***
	(0.0115)	(0.0125)
Obs.	378	378
R^2	0.4550	0.4670

OLS regression analysis results. Significant coefficient estimates at ***1%, **5%, *10%. Standard errors clustered at session level in regression 9, and at preference-profile level in regression 10 (between parentheses) efficiency levels achieved in each treatment (for completeness, in cost treatments, we also present the levels net of search costs).

Several points are of note here. First of all, a low information level is associated with slightly higher levels of efficiency, unless low information is combined with costly proposals and a large market size. Moreover, and quite surprisingly, treatments with commitment correspond to the highest efficiency levels, followed by treatments without frictions, whereas costly proposals tend to induce the lowest efficiency levels.

For a statistical analysis of our treatment variables, we again turn to regression analysis. Table 8 shows the estimated coefficients for two ordinary-least-squares regressions. In both regressions, the dependent variable is our proxy for efficiency, the proportion of the achieved aggregate payoff in the highest possible level. The independent variables are the number of rounds played, the dummy variables for the level of information, frictions, and market size (regression 9), as well as cross-effects (regression 10).

The coefficient estimates for the independent variable "round" are significant and positive, so that experience is efficiency-enhancing. Low information does not seem to have a large and significant impact on efficiency. In contrast to the first impression based on results in Table 7, coefficients associated with search costs and its cross-effects are not statistically significant. However, coefficients associated with commitment tend to be positive, relatively large and statistically significant. As for the effect of a large market size is less clear. The results from the regressions show that a large market size has no significant impact on efficiency.

The observed efficiency levels in treatments S1, S4, L1 and L4 do not seem to differ dramatically from the hypothesized 90.9%. This is in line with our Hypothesis 3, according to which the level of information and market size do not affect the proportion of efficient matchings.[25]

Result 3. *The level of efficiency is not significantly lower in large-market than in small-market treatments. Low information and search costs do not impact efficiency significantly. Nevertheless, commitment has a clear positive effect on efficiency. Finally, experience is also efficiency-enhancing.*

Binary comparisons for our treatment variables in terms of the efficiency of the market outcome support the above findings. They suggest that, among our treatment variables, only commitment and market size have significant impact on the efficiency of the market outcome. Table 3 in Supplementary material reports the resulting *p*-values from *t*-tests for means and the Kruskal-Wallis equality-of-populations rank tests.

[25] The *p*-values from *t*-tests are 0.11, 0.69, 0.04 and 0.39 for the above-mentioned four sessions, respectively. Although the difference of the observed efficiency level from the expected one seems to be statistically significant at 4% for our treatment with low information, the size of the effect is not large.

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 the pace of proposals 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 proposals have a negative impact on stability of the final matching, but do not deter markets from finding their way to an efficient outcome. Surprisingly, commitment enhances efficiency considerably, while reducing stability only in some instances (i.e., treatments). On the other hand, low information on 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 the desirable properties of the market outcome. For instance, the combination of low information levels and costly search is particularly detrimental to stability. Therefore, the benefits of introducing a centralized clearinghouse in markets that exhibit these features are potentially high.

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