Ignorance is Strength: Improving Performance of Decentralized Matching Markets by Limiting Information*

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Abstract

I develop a model of a decentralized matching market in which heterogeneous buyers pursue sellers by requesting services. Buyer requests are perfectly coordinated. Sellers have preferences over buyers and independently choose which buyers to accept. Preference heterogeneity induces same-side and cross-side externalities leading to sellers' excessive screening and welfare loss. Platform's policy of coarse revelation of buyer information improves welfare by decreasing the ability of sellers to "cherry-pick" desirable buyers. Implication for welfare-maximizing platform is to limit information to the sellers when they are the more patient and more substitutable side of the market.

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However, if sellers have unobserved heterogeneity, coarsening is effective only if sellers are tightly capacity constrained or buyer-to-seller ratio is large. An approach for the problem of optimal disclosure with heterogeneous forward-looking agents with general type distribution is developed.

1 Introduction

In decentralized matching markets, such as markets for lodging, labor market, dating market and others, information availability about goods or trading partners is the key. Complete information lets the participants identify and pursue the most valuable opportunities. Online platforms spend a lot of resources eliciting match-relevant information from the users. However, sometimes this information is not fully revealed to the users. For example, Uber drivers do not see the passenger destination even if it was put in. Workers on online temp agencies, such as TaskRabbit, commit to broad categories of tasks without knowing the exact details of potential jobs. What is the rationale for these design decisions? What is the right information intermediation policy for the platform that cares about both sides of the market? What does it depend on?

I study the information intermediation problem in the context of the following model. Buyers have needs for a service and request sellers who want jobs. Buyers are short-lived, have to match fast but are indifferent about which seller completes their task. Sellers are long-lived, don't care about speed but have heterogeneous preferences over buyers; in particular, not all buyer jobs are profitable. Buyers contact sellers, sellers review buyer attributes and choose to accept or reject the buyer request. Sellers have limited capacity for serving buyers: if a seller accepts a job, he becomes unavailable for a period of time and cannot accept new jobs. The platform designs an information disclosure policy that governs what buyer attributes are disclosed to sellers before they decide to accept or reject the buyer request. I consider the general platform's objective of maximizing the weighted average of buyer surplus and seller profits.

Full information disclosure need not be optimal because, besides positive effect on the seller match quality, information disclosure may negatively affect the match rate. Seller profit is a product of match quality and match rate, and the buyer surplus in the base model is an increasing function of the match rate. Sellers maximize profits, and so their payoff function does not align with the platform's objective. Namely, sellers tend to reject ineffectively many jobs, or *cream-skim*. Unlike sellers, the platform cares about welfare on both sides of the market. If negative effects of information disclosure on the match rate are strong, the efficient disclosure is coarse. In this paper, I study the optimal disclosure policy for different specifications of the seller side of the market.

Efficiency requires that both match quality and match rate are high. Seller profit is larger when both match quality and match rate are significant, and the buyer surplus is large when the match rate is high. However, match quality and match rate are in conflict. On the one hand, enforcing higher match rate requires sellers to accept more jobs. As a result, seller match quality degrades because they need to accept more inferior jobs. On the other hand, letting sellers pick the most valuable buyers leads to high rejection rates. High rejections rates imply low match rates. For example, on Uber, if drivers often reject passenger requests, passengers will have long wait times. On Airbnb, if hosts often reject guest inquiries, guests have to spend more time and effort searching.

Optimal disclosure policy must balance between three effects: the positive effect on the seller match quality, and the negative static and dynamic effects on the match rate. First, the positive effect of disclosure on the seller match quality is straightforward. From a seller's point of view, more information increases his set of attainable payoffs. Holding the match rate fixed, he individually benefits from more information about buyers. Second, information disclosure reduces the platform's ability to induce sellers to accept more jobs. Namely, the platform can coarsen information to increase the seller expected marginal profit. Ignoring dynamic effects, higher marginal profit induces sellers to accept more jobs, which leads to higher match rates. Third, more information available to sellers increases their return to search. Therefore, the opportunity cost of accepting is higher, because acceptance precludes further search. As a result, sellers reject more often, and the match rate goes down. This dynamic effect on match rate arises only when sellers have limited capacity and are forward-looking. The match quality effect gives a motive for the platform to disclose information, while the match rate effects give the motive to coarsen information.

If sellers are identical, then some information coarsening is always optimal. Coarsening is necessary whether the platform maximizes the welfare, or the buyer surplus, or the joint seller surplus (see Figure 2). For welfare maximization, the optimal policy involves pooling inframarginal profitable jobs with marginal unprofitable but efficient jobs. This kind of coarsening increases seller expected marginal profit and induces higher acceptance rate, and consequently higher match rate. The efficient disclosure is the intermediate case between buyer-optimal disclosure and seller-optimal disclosure. For the buyer-surplus maximization, coarsening is necessary because sellers underweigh the importance of the match rate to buyers in their payoff function. Coarsening degrades seller match quality but increases the match rate. Therefore, buyers benefit from coarsening. When buyer search costs are higher, it is efficient to coarsen more because rejections are more costly to buyers. Interestingly, for the joint seller profit maximization, the optimal disclosure is also coarse.

The negative effect of disclosure on joint sellers profits is a form of seller coordination failure. In a marketplace where sellers act independently, each seller keeps his schedule open by rejecting low-value jobs to increase his own chances of getting high-value jobs. As a result, sellers spend a lot of time waiting for the high-value jobs. Collectively, this behavior is suboptimal because all profitable jobs have to be completed. I attribute the source of the coordination failure to what I call the *cream-skimming externality*: By rejecting a job, a seller remains available on the marketplace and attracts a fraction of subsequent buyers, who otherwise would go the other sellers. As a result, the other sellers face fewer profitable jobs and obtain lower profits. The cream-skimming externality arises only when sellers are capacity constrained and forward-looking. When the cream-skimming externality is present, sellers underestimate the effect of their own acceptance rate on the platform-wide match rate. Therefore, the sellers resolve the match quality-match rate tradeoff collectively sub-optimally. Coarsening information decreases opportunity cost of rejecting and increases the match rate to the seller-optimal levels.

When sellers have unobserved heterogeneity, the optimal disclosure is finer than in the case of identical sellers. With heterogeneous sellers, the match quality effect of information disclosure is stronger, but there are subtleties. Coarse disclosure tailored to increase one seller's acceptance rate can drive another seller's average profit below zero and violate his individual rationality constraint. What coarsening is optimal, if any, is now not obvious. The optimal policy should accommodate the possibly opposite reactions of sellers to disclosure and will depend on the shape of the seller type distribution.

To understand how seller heterogeneity affects optimal disclosure policy, I study the linear payoff environment, with vertically differentiated buyers and vertically differentiated sellers. In this case, the optimal disclosure policy depends on the shape of seller type distribution as well as on the intensity of buyer traffic and the tightness of seller capacity constraints. Here, seller match payoff is $y - x$, where y is seller type and x is buyer type, and buyer match payoff is constant. I first consider the case of uniform distribution of seller types, where I can fully characterize the optimal disclosure policy.A key result of my model is that with the uniform distribution of sellers, the match-rate maximizing disclosure policy is *upper-coarsening*: high buyer types are pooled, and low buyer types are revealed truthfully. This is in stark contrast with the case of unconstrained sellers, in which information disclosure does not affect the match rate (cf. Kolotilin *et al.* (2015)). When buyer-to-seller ratio is high or when the sellers are more capacity constrained, the efficient disclosure is also upper-coarsening. In the converse case, the efficient disclosure is the full disclosure.

Turning next to general (non-uniform) distribution of sellers, I find that depending on the distribution, optimal disclosures can have a variety of qualitatively different shapes, and can be very complex. The heuristic in the case of unconstrained sellers is to pool buyer type on the increasing part of buyer probability density function g, and reveal buyer type on the decreasing part of g. With capacity constrained sellers, this heuristic should be further qualified with seller utilization rates. Despite the complexity I find the first-order condition for the general case in Lemma 3.

The model is mainly motivated by the matching problems of digital marketplaces. As one example, on Airbnb, guests (buyers) are differentiated by age, gender, race, personality, etc.; hosts (sellers) have the preference for gender, race, lifestyle, etc. On the one hand, guests prefer the hotel-like experience when they can book a listing instantly. On the other hand, hosts want to avoid troublesome or inconvenient guests. Airbnb introduced InstantBook feature to satisfy the guests' demand for convenience. In my model, it corresponds to the no disclosure policy. However, one can imagine a finer tool that would allow a host to specify the guest segments who can instantly book his listing. The problem of optimal guest segments is equivalent to the problem of the optimal information disclosure, and, as I argued above, has important tradeoffs. Another example is Uber's matching system. Uber sends passenger (buyer) requests to drivers (sellers) and includes to the request information about the passenger. In the current version of UberX, the passenger's destination is not shown to drivers although it is payoff relevant piece of information. Another example is on-demand labor platforms, such as TaskRabbit. On TaskRabbit, the freelancers commit to an hourly rate over a broad category of tasks, such as Moving. The breadth of categories is equivalent to the coarseness of the platform's signal about the client's task, and so can be analyzed using my framework.

The contribution of the present paper is two-fold. First, the paper explains the role of information intermediation in decentralized matching markets. It shows that strategic information disclosure can be an effective tool to balance the seller's demand for more transparency and buyer's demand for less hassle and more speed. Simultaneously, it can alleviate the seller coordination failure by offsetting the cream-skimming externality.

The paper's technical contribution is to the literature of information design. The paper extends the model of signaling game with heterogeneous audience to the case with endogenously available and dynamically optimizing receivers. In this case, the design of the optimal information disclosure is a non-trivial problem. With forward-looking receivers, information disclosure policy determines not only the receiver's stage payoff but also the distribution of his potential future payoffs. As a result, receiver's decision to accept depends not only on the posterior mean of the state but also on the entire signaling structure. This makes the concavification approach of Kamenica and Gentzkow (2011), as well as the linear programming approach of Kolotilin (2015) unsuitable for the analysis of my model. I approach it by representing signaling structures as a particular class of convex functions and then using the calculus of variations to find the first-order necessary conditions. Section 3.5 sketches the main steps of the approach.

The rest of the paper is organized as follows. Section 2 introduces the model of decentralized matching market, and establishes the existence and uniqueness of equilibrium. Section 2.4 contains the discussion of the key assumptions of the model. Section 3 sets up the platform's information disclosure problem, solves and explains it in different settings. First, Section 3.1 explains the seller coordination failure. Then, Section 3.2 studies the setting with identical sellers, and Section 3.3 discusses the competing effects of information disclosure . Section 3.4 studies the setting with heterogeneous sellers and presents the main characterization result of the paper. Section 3.5 describes the technique for proving the main theoretical result. Section 4 concludes.

2 The Model of Decentralized Matching Market

In this section I lay out a model of a decentralized matching market that will allow me to evaluate how information disclosure policy affects the equilibrium market outcome. The model has two main components: the matching process between buyers and sellers, and the seller optimization problem. In the end of this section I define the steady state equilibrium, in which seller actions are individually optimal, and the dynamic matching system is in steady state.

2.1 Setup

Spot matching process. There are three parties involved in the search and matching process: sellers, buyers and the platform itself. Time is continuous.

There is mass 1 of sellers, who always stay on the platform, never leave or arrive. The sellers do not actively look for jobs, but instead screen the buyer requests: each worker is presented with a sequence of job offers at Poisson rate, and decides whether to accept or reject them to maximize discounted profit flow. At each moment of time a seller is either available and waits for new jobs, or busy working on a job. An accepted job takes time τ to complete, during which time the seller cannot receive new jobs. This is the main source of matching friction. In what follows, I also refer to τ as the seller capacity constraint because higher τ implies the seller can complete fewer jobs over the same period of time.

There is a continuum of potential buyers who gradually arrive over time at flow rate β: within time interval dt, mass βdt of buyers arrive to the platform. Each new buyer arrives with a single job that he proposes to one of the available sellers. The seller is chosen uniformly at random from the pool of available workers. If the buyer's job is accepted, the buyer stays until his job is completed, otherwise he leaves the platform. Assume $\beta\tau < 1$ which implies that collectively, it is physically possible for sellers to complete every buyer job. See the detailed discussion of the assumptions on buyer search and buyer arrival rate in Section 2.4 below.

The platform does not use the centralized matching process, instead it makes disclosure of buyer characteristics part of its design, as described below. See figure 1a for the illustration of the matching process.

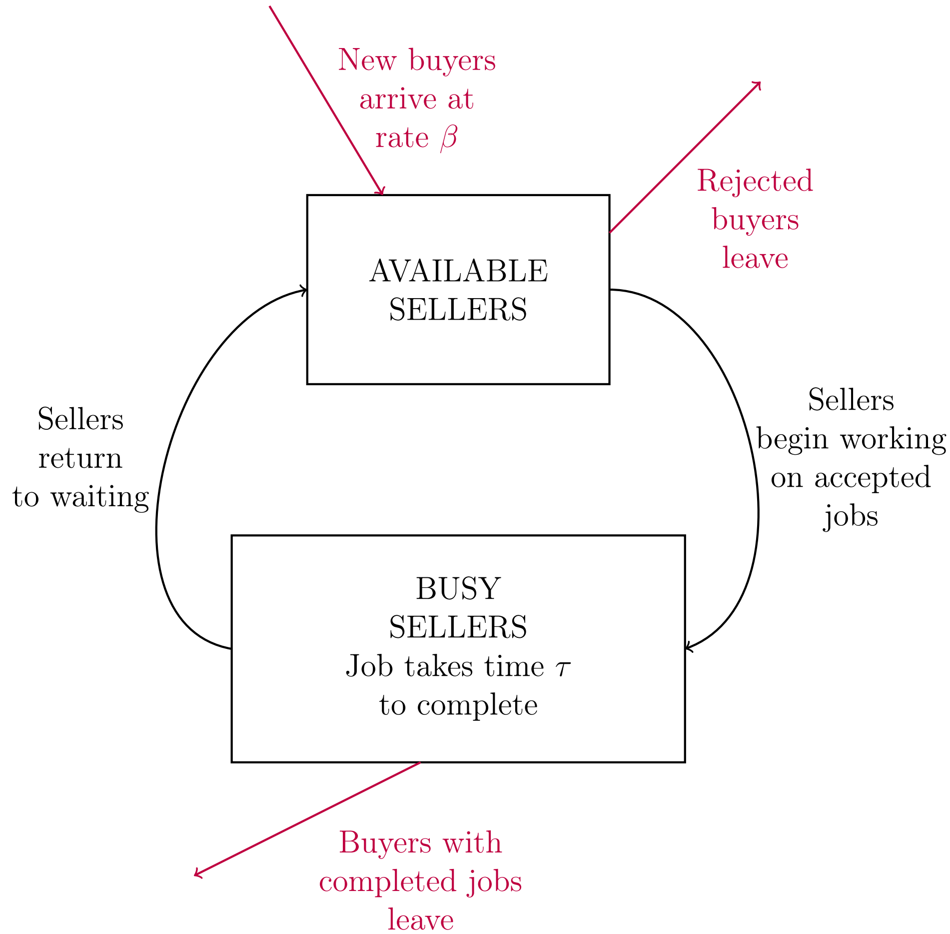
Buyer and seller preference heterogeneity. There are two dimensions of heterogeneity in the market. First, each seller has heterogeneous match payoff across buyers. Second, different sellers have different payoff functions over jobs. Concerning the platform's information disclosure problem, I need the following pieces of notation. Let x be buyer type, with the interpretation that x is buyer characteristics observed by the platform.[1] The space of buyer types X is a compact subset of a Euclidean space. The distribution of x is F with full support. Let y be seller type, with the interpretation that y is seller characteristics unobserved by the platform.[2] The space of seller types Y is a compact subset of a Euclidean space. The distribution of y is G with full support that admits density g, g is differentiable on Y. Seller profit for one match is $\pi(x, y)$. Assume π is continuous and for any y there is x such that $\pi(x, y) > 0$. Buyer net match payoff is $u(x, y)$. Assume that all incoming buyers have non-negative match payoff:

$$u(x, y) \geqslant 0. \tag{1}$$

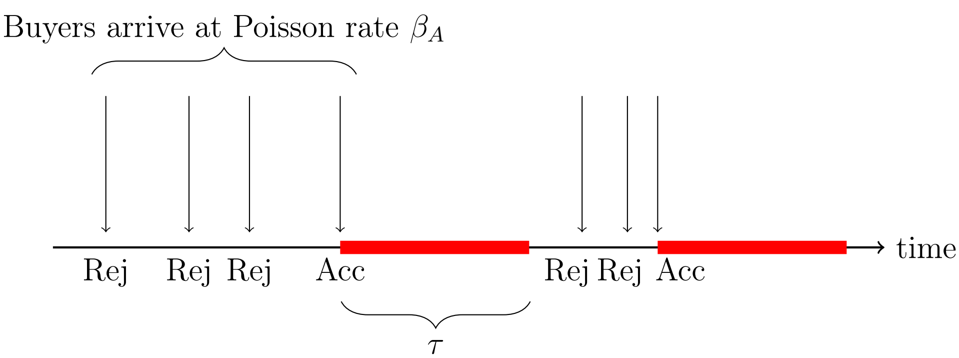
Platform: Information intermediation. Before the matching process starts running, the platform designs and commits to a disclosure policy that governs how buyer characteristics are disclosed to sellers. The platform observes buyer type x and sends a signal about x to the seller. The seller does not receive any additional information about x besides the platform's signal. Let $S = \Delta(X)$ be the set of all posterior distributions over X. *Information*

[1] Buyer type x captures the payoff-relevant information the platform elicits from the buyer about the job, passively from the buyer's cookies and queries or actively by asking questions. For example, on Uber, x would include rider's destination; on Airbnb, x would include guest's race, age and gender.

[2] Seller type y captures the payoff-relevant information the platform did not elicit from sellers by whatever reason – costly, unethical, etc. For example, on Uber, y would include the driver's preference for long rides and traffic; on Airbnb, y would include the host's preference for his guest's age, gender, socio-economic status, race, etc.



(a) Spot matching process. Buyers arrive at exogenous rate β, and contact available sellers. If rejected, a buyer leaves the platform. If accepted, the buyer forms a match which lasts for time τ. After the time elapses, the buyer leaves the platform, and the seller returns to waiting.



(b) Seller dynamic optimization problem with screening and waiting. An available seller receives requests at Poisson rate β_A. If a request is accepted, the seller becomes busy for time τ during which he does not receive new requests.

Figure 1: The model of decentralized matching market has two main components: the spot matching process, and the seller dynamic optimization problem.

disclosure policy $\lambda \in \Delta(S)$ is a probability distribution of posteriors.[3] The interpretation is that $s \in S$ is the platform's signal to the seller, and so $\lambda(S')$ is the fraction of buyers with signals $S' \subset S$.[4] Note that a disclosure policy can be seen as a two-stage lottery on X whose reduced lottery is the prior F. The set of possible disclosure policies is then:

$$\left\{\lambda \in \Delta(S) \colon \int s\, d\lambda(s) \sim F\right\}.$$

When a buyer of type x arrives, the platform draws a signal according to λ and shows it to the seller. The seller knows the platform's choice of λ, and so his interpretation of a signal as a posterior is correct. The full disclosure policy, denoted by λ^{FD}, perfectly reveals buyer type x to the sellers. No disclosure policy fully conceals x. Disclosure policy λ' is *coarser* than λ'' if λ' is a Blackwell garbling of λ''. That is, the platform can obtain λ' from λ'' by taking λ'' and pooling some x's.

Steady state distribution of sellers. The matching process is the dynamic system in which sellers become repeatedly busy and available. A steady state of the matching process is characterized by the fraction of available sellers of every type and their acceptance rates. Formally, let $\alpha(y) \geqslant 0$ be the *acceptance rate* – a fraction of buyers accepted by type-y sellers. Let $\rho(y)$ be the *utilization rate* – the fraction of type-y sellers who are busy. Denote the average utilization rate by $\bar{\rho} := \int_Y \rho(y) dG(y)$. Since the total mass of sellers is 1, $\bar{\rho}$ is also the mass of busy sellers.

In a steady state, the flow of sellers who begin working is equal to the flow of sellers who finished the job and return to waiting. The flow of beginning sellers is equal to the buyer flow to type-y sellers times type-y sellers' acceptance rate. Since buyers distribute uniformly

[3] When X is a compact subset of a Euclidean space, $\Delta(S)$ is the set of Borel probability distributions with the weak-* topology on $\Delta(X)$.

[4] I focus on the "public" signaling when the same λ applies to all seller. I am not studying the mechanism design problem where the platform tries to elicit or learn the seller's type y and tailor the disclosure policy to seller type. Kolotilin *et al.* (2015) find in the one-shot signaling game with linear payoffs that public signaling is equivalent to private signaling.

across the available sellers, the buyer flow to type-y sellers is $\beta\frac{(1-\rho(y))g(y)}{1-\bar{\rho}}$. The acceptance rate is $\alpha(y)$. Thus, the beginning flow is $\beta\frac{(1-\rho(y))g(y)}{1-\bar{\rho}}\alpha(y)$. The flow of returning sellers is $g(y)\rho(y)/\tau$ because the mass of busy y-sellers is $g(y)\rho(y)$, and jobs are completed in time τ. In a steady state, the flow of beginning sellers is equal to the flow of returning sellers:

$$\beta\frac{(1-\rho(y))g(y)}{1-\bar{\rho}}\alpha(y) = \frac{g(y)\rho(y)}{\tau}, \quad \forall y \in Y. \tag{2}$$

Seller dynamic screening problem. Denote by β_A the Poisson rate at which buyer arrive to an available seller. Since buyers contact only available sellers, β_A depends on the mass of available sellers. In a steady state, the mass of available sellers is $1-\bar{\rho}$, and so,

$$\beta_A := \frac{\beta}{1-\bar{\rho}}. \tag{3}$$

Note that β is the flow rate at which buyers arrive to the platform, while β_A is the Poisson rate at which buyers arrive to available sellers.[5] The particularly simple form of the relation between the two in Eq. (3) follows from the uniform distribution of buyers across available sellers. Sellers take β_A as given because there is a continuum of sellers on the platform, and any individual seller's actions do not affect β_A.

A risk-neutral seller solves the dynamic optimization problem to maximize the average profit flow. The seller faces the sequence of jobs arriving at Poisson rate β_A, for each job observes the platform's signal s and chooses to accept or reject it. See figure 1b for the illustration. Denote by $\pi(s,y) = \int_X \pi(x,y)ds(x)$ the seller y's expected profit if he accepts a job with signal s. Denote by $V(y)$ be the average profit flow when seller of type y acts optimally (the value function)[6]. Let $v(s,y)$ be the value of a new job with signal s, where

[5] In more detail, on the one hand, an individual available seller faces a stochastic arrival process, such that the probability of arrival of a new buyer over time interval dt is $\beta_A dt + o(dt)$. On the other hand, available sellers jointly face the deterministic arrival process of buyers, such that over time interval dt the mass $\beta_A dt$ of buyers arrive.

[6] For example, if a seller earns \$1 on each job, and time interval between starting consequent jobs is 2, then $V(y) = 1/2$.

v includes the option value of rejecting the job and the opportunity cost of accepting. The value of a new job is zero if the seller rejects it, and $\pi(s,y) - \tau V(y)$ if he accepts it, where $\tau V(y)$ is the opportunity cost of accepting due to being unavailable for time τ. Therefore, $v(s,y) = \max\{0, \pi(s,y) - \tau V(y)\}$. The average profit per unit of time equals the expected value from one job times the expected number of new jobs: $V(y) = \beta_A \mathbb{E}[v(s,y)]$.[7] Put together, the seller optimization problem is given by:

$$V(y) \;=\; \beta_A \int \max\{0, \pi(s,y) - \tau V(y)\} d\lambda(s). \tag{4}$$

The seller strategy is function $\sigma(\cdot, y) \colon S \to [0,1]$ that for every seller type y maps signal to the probability of accepting it. The seller acceptance rate is the ex ante probability of accepting a job:

$$\alpha(y) = \int \sigma(s,y) d\lambda(s). \tag{5}$$

2.2 Examples of marketplaces

In this section I explain how the model fits the marketplaces of Uber, Airbnb and labor platforms, such as TaskRabbit. I will return to these applications after I state my main results in Section 3. Recall that y captures the seller heterogeneity unobserved by the platform, and x captures buyer heterogeneity observed by the platform.

Uber. When idle, drivers receive requests from passengers. Type y includes driver home location, preference for long rides, tolerance to congestion; x includes passenger's destination and his ride history. Price per mile and minute is fixed (conditional on aggregate multiplies, such as surge pricing). Drivers do not like very short rides or the rides to the remote neighborhoods. Passengers do not like waiting. Concealing passenger destination from drivers is information coarsening.

[7] I consider time average payoff rather than discounted sum because discount rate is not essential for my argument. However, the results immediately generalize to the case when the seller has discount rate r by replacing τ with $\tau_r = \frac{1-e^{-r\tau}}{r}$.

Airbnb. Hosts are capacity constrained in rooms: once a room is booked for a specific date, the host cannot accept a better guest. Type y includes host's preference for age, race, personality, daily schedule. Type x includes guests' gender, age, socio-economic status, lifestyle. Every host sets his own price that applies to all guests but he may prefer to reject certain guests who he expects will be a bad fit. The InstantBook feature, if adopted by a host, is effectively the no disclosure policy because the host commits to accepting all guests.

TaskRabbit. The service providers are capacity constrained in the number of tasks they can do per week. Once a service provider agrees to do one task, he is constrained in picking new tasks. Type y includes service provider's skill and work ethics. Type x includes job category, job difficulty, client's professionality and location. Service providers set hourly rate that apply to all tasks in the same category. Making service providers to commit and price to broad categories is a form of information coarsening.

2.3 Equilibrium definition and existence

A steady state equilibrium is a market outcome in which the sellers take buyer arrival rate β_A as given and optimize independently, and the seller busy-available flows balance out. Formally, a tuple $(\sigma, \bar{\rho})$ constitutes a *steady-state equilibrium* if

1. [Optimality] For every type-y seller for all y, $\sigma(\cdot, y)$ is an optimal strategy given buyer Poisson arrival rate $\beta_A = \beta/(1-\bar{\rho})$.

2. [Steady state] Average utilization rate $\bar{\rho}$ arises in a steady state when sellers play σ, as shown in $\{(2), (5)\}$.

Proposition 1. *A steady-state equilibrium exists. It is unique up to the acceptance of marginal jobs in the following sense. If $(\sigma^i, \bar{\rho}^i)$, $i = 1, 2$ are two steady-state equilibria, then (1) $\bar{\rho}^1 = \bar{\rho}^2$, and (2) for any $y \in Y$, $\sigma^1(\cdot, y)$ and $\sigma^2(\cdot, y)$ coincide except on $\{s \colon \pi(s, y) = \tau V(y)\}$.*

To prove the result, first, show that for an arbitrary vector of acceptance rates $\alpha(y)$, there is a unique steady state value of $\bar{\rho}$ (Lemma 5). Then, average utilization $\bar{\rho}$ is increasing and continuous in $\alpha(y)$ for any $y \in Y$. The uniqueness of equilibrium follows from monotonicity of reaction curves of α in $\bar{\rho}$ and $\bar{\rho}$ in α. Namely, if average utilization $\bar{\rho}$ is higher, then buyer traffic to each available worker is higher; sellers become more picky and acceptance rate $\alpha(y)$ decreases. As $\alpha(y)$ increases, sellers become less available, that is $\bar{\rho}$ is lower. For details see the proof in the Appendix on page 38.

2.4 Discussion of the modeling assumptions

In this subsection I discuss in detail the important assumptions of my model. The assumptions are motivated by the stylized facts about the online platforms.

Assumption 1. *Buyers make a single search attempt.*

Rejection-intolerant buyers is a simplifying assumption that helps me avoid having an endogenous distribution of buyer types. It captures a real aspect of matching markets that rejections are costly to buyers, e.g. wasted time, wasted search effort, bidding costs, etc. Moreover, buyers often do take rejections badly. For example, Fradkin (2015) reports that on Airbnb, an initial rejection decreases the probability that the guest eventually books any listing by 51%.[8]

Assumption 2. *Buyers contact available sellers only.*

The goal of the paper is to explore the matching friction that pertains to preference heterogeneity and screening. Therefore, I assume away the coordination friction owing to simultaneity, when several buyers request the same seller at the same time. Also, I assume away the coordination friction owing to unavailability, which arises when buyers request unavailable sellers who did not update their status or do not have the means to do so. The

[8]The results would generalize if buyers return for consequent search attempts. If buyer make several search attempts, then buyer arrival rate is effectively increased. Sellers still cream-skim but information coarsening is even more effective because higher buyer arrival rate means higher seller option value of rejection.

coordination frictions in matching markets have been extensively studied in the theoretical literature (Burdett *et al.* (2001); Kircher (2009); Halaburda *et al.* (2015); Arnosti *et al.* (2014)), and digital platforms usually have good technological means of resolving the simultaneity driven friction[9] . I assume away the simultaneity and unavailability driven frictions to focus on screening.

Assumption 3. *Buyers contact an available seller chosen uniformly at random.*

This is a simplifying assumption that lets me focus on the supply side of the market and keeps the base model clean. The assumption has two implications. First, the seller of any type faces the same intensity of buyer traffic β_A. Second, each seller faces the same distribution of buyer jobs F.

Assumption 4 (No Excess Demand)**.** *Collectively, it is physically possible for sellers to complete every buyer job:* $\beta\tau < 1$

The assumption makes the exposition cleaner and does not add more insights. Relaxing it requires more notation to deal with either automatic rejections or queues. I do this in Appendix D and show that qualitatively results do not change.

[9]E.g. Fradkin (2015) finds that on Airbnb the coordination friction explains only 6% of failed matches.

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