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 what 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 market for lodging, labor market, dating market and others, information availability about goods or trading partners is the key to the well-functioning market. Complete and symmetric information facilitates trade by letting the market participants identify valuable opportunities, and preventing adverse selection effects (Akerlof 70, Roth (2008)). However, availability of information increases returns to search and screening, and they need not accrue symmetrically to the sides of the market. In fast-moving markets, *excessive screening* is an important source of market failure. As a stark example, on Airbnb, guests are 51% less likely to eventually book conditional on being rejected from their first request; still, 20% of guest inquiries are screened by hosts (Fradkin (2015)). On Uber, passengers are highly sensitive to wait times (Hall *et al.* (2015)). Rejections and long delays reduce buyer surplus and decrease buyer participation on the marketplace, and the effect is amplified in two-sided markets due to network effects. Can the platform design an information disclosure policy to alleviate the excessive screening problem and improve welfare (revenue, matching rates)? What does the optimal disclosure policy depend on?

The efficient information disclosure must balance two opposing forces—sellers' demand for information about heterogeneous buyers, and damage to buyers from the sellers' cream-skimming behavior. On the one hand, disclosure of buyer characteristics uncovers buyer heterogeneity and allows sellers to identify matches they value the most. This increases seller surplus. On the other hand, disclosure increases the seller opportunity cost of accepting a match, as acceptance precludes further search. When the sellers' preferences for matches are not aligned with the buyers', or when buyers have higher cost of rejection (e.g. due to higher time-sensitivity), meticulous screening harms buyer surplus. It has been recognized in the information economics literature that the latter, "strategic", effect of information disclosure can outweigh the former, "individual choice", effect (Bergemann and Morris (2016)). If that is the case, then information coarsening is a welfare-improving intervention. When little information is available, the sellers settle for less and screen faster. Despite the fact that information intermediation is potentially powerful design tool, the implications of this general observations to the context of decentralized matching markets have not been well explored.

In this paper I develop a model of information intermediation in decentralized matching markets to formalize the information disclosure tradeoffs and to characterize the optimal disclosure policy for a class of decentralized matching environments. Section 2 sets up a model in which short-lived buyers gradually arrive over time and pursue long-lived sellers by proposing jobs. Sellers have heterogeneous preferences over jobs and independently decide what jobs to accept. Sellers have limited capacity: if a seller accepts a job, he becomes busy for a period of time and cannot accept new jobs. Buyer and seller preferences over matches are not aligned: some matches are unprofitable for sellers but are valuable to buyers. In contrast to many search-and-matching models that have a coordination friction as the main matching friction (Burdett *et al.* (2001); Kircher (2009); Arnosti *et al.* (2014)), I assume no coordination friction: only available sellers receive buyer requests. The assumption is motivated by the observation that most digital platforms have good technological means of solving the coordination problem.[1] The key matching friction of the model thus pertains to preference heterogeneity.

The platform uses information disclosure policy as a design tool. Before the matching process starts running, the platform commits to a disclosure policy that governs what buyer information sellers observe prior to the acceptance decision. The policy is modeled as a signaling game between the platform and the sellers, building on Kolotilin *et al.* (2015). The new element is the seller dynamic optimization and endogenous availability. I consider the general platform's problem of maximizing a weighted average of expected buyer surplus and expected seller profits, which embeds the problems of maximizing welfare, seller joint revenue and the number of matches.

The model is mainly motivated by the matching problems of digital marketplaces. As

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

one example, on Airbnb, guests (buyers) are differentiated by age, gender, race, personality, etc.; hosts (sellers) have preference for gender, race, life style, 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 meaningful 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 concurrent 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 a hourly rate over a broad category of tasks, such as Moving. The breadth of categories is equivalent to coarseness of the platform's signal about the client's task, and so can be analyzed using my framework.

If sellers are identical, then some information coarsening is always optimal. In this case, as shown in Section 3.2, the efficient coarsening involves pooling inframarginal profitable jobs with marginal unprofitable but efficient jobs. This way, sellers' actions get aligned with the platform's objective. When buyer search costs are higher, it is efficient to coarsen more because the set of efficient matches is larger. The situation is more subtle when sellers may have payoff heterogeneity unobserved by the platform. In this case, information coarsening tailored to increase the acceptance rate of one seller can overburden another seller and violate his individual rationality constraint. What coarsening is optimal, if any, is now not obvious, as the optimal policy depends on the distribution of seller types and should accommodate the possibly opposite reactions to the same disclosure policy.

To understand how seller heterogeneity affect 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 payoff is constant. With the uniform distribution of seller types, as shown in Section 3.4, the optimal match-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 static case, in which information disclosure does not affect the number of matches (cf. Kolotilin *et al.* (2015)). When buyer-to-seller ratio is high or the seller capacity constraints are tighter, the efficient disclosure is also upper-coarsening. In a converse case, the efficient disclosure is the full disclosure. For the general distribution of seller types, the optimal disclosure depends on whether probability density function of seller types is decreasing or increasing and the seller utilization rates, and has the spirit of "anything goes" result. Nevertheless, I give the first-order condition for this general case in Lemma 3.

Disclosure to sellers has three competing effects on welfare, with the optimal disclosure determined by what effect is dominant. The first effect is the standard *Individual Choice effect* operating on the seller side of the market. From an individual seller's point of view, more information increases his set of attainable payoffs (Blackwell (1953)). Holding the other sellers' behavior fixed, he individually benefits from more information about buyers. The second effect of information disclosure is the *Buyer-side effect*. More information available to sellers reduces the platform's ability to induce sellers to accept buyer-valuable jobs. The third effect is the *Seller Option Value effect*, which is novel to the persuasion literature, and arises only with capacity constrained sellers. More information available to sellers increases their ability to "cream-skim" the stream of jobs and increases the option value of rejection. In equilibrium, the Option Value effect leads to a range profitable jobs being rejected, which hurts the joint seller surplus. The Buyer-side and the Option Value effect are the instances of a general principle that revealing more information to sellers imposes more constraints on the designer and reduces the set of outcomes he can induce (Bergemann and Morris (2016)). Both the Buyer-side and the Option Value effects lead to sellers' excessive screening — rejection rates are inefficiently high. Therefore, the Buyer-side and the Option Value effects give a motive to the platform to coarsen information. On the contrary, the Individual Choice effect gives a motive to disclose information.

Negative effects of disclosure on sellers (the Option Value effect) 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 individual 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. The source of the coordination failure is 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 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 future potential 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 certain class of convex functions and then using calculus of variations to find the first-order necessary conditions. Section 3.5 sketches the main steps of the approach.

Related Literature. The paper contributes to search and matching in markets and information design strands of economic literature. There have been studies on matching markets in the literatures of economics and operations research. To the best of my knowledge, no prior work has explored in detail the information disclosure as a design tool in a search-and-matching setting.

Hoppe *et al.* (2009) show that the option of disclosing information leads to wasteful signaling, that can in certain cases overcome the benefits from improved matching. However, they consider a black-box matching function and only two information structures, full disclosure and no disclosure. Shimer and Smith (2001) study a model of decentralized search market with heterogenous preferences, and similarly to my work, have the matching friction owing to a screener's private benefit of waiting being the increased quality. However, they study taxes as the intermediary's intervention policy. Theoretical results in economics of labor and housing, such as Burdett, Shi and Wright (2001), Albrecht, Gautier and Vroman (2006), and Kircher (2009), show that markets where sellers have limited capacity are inherently more frictional than markets with large firms. However, the main cause of inefficiency in these papers is mis-coordination due to simultaneity and unavailability. Halaburda (2010); Arnosti *et al.* (2014) propose to limit the intensity of applications to allay this friction. On the contrary, I focus on the matching friction owing to preference heterogeneity. In matching marketplaces, evidence suggests that although the first-order effect of information availability is positive (Lewis (2011), Tadelis and Zettelmeyer (2015)), the problem of failed matches can be severe (Fradkin (2015); Horton (2015); Cullen and Farronato (2015)).

On the methodological side, my work relies and extends the literature of communication in games (Aumann *et al.* (1995); Grossman and Hart (1980); Milgrom (1981); Kamenica and Gentzkow (2011); Rayo and Segal (2012); Bergemann and Morris (2013); Kolotilin *et al.* (2015)). The most closely related paper is Kolotilin *et al.* (2015) from where I adopt the framework of the signaling game with heterogeneous audience by extend it to the case with forward-looking and endogenously available receivers. Although forward-looking, the receivers receive one signal per job, which differs my work from the gradual learning settings of Ely 2015 and Smolin (2015). Rayo and Segal (2012) study the setting with arbitrary complementarities between the sender's and receiver's payoffs and show that the sender-optimal disclosure policy pools "non-ordered prospects". Compared to them, I have a simpler sender's payoff function, all prospects are "ordered" in their language, but a multiple-agent and dynamic receiver side.

The paper is related to the broader literature of information disclosure in markets. The seminal papers of Akerlof 1970 and Hirschleifer 1971 highlighted possible opposing effects of coarse information on welfare (adverse selection and risk-sharing, respectively). In advertising, the effects of better targeting is ambiguous because it affects both demand and supply. On the one hand, better targeting increases demand for advertising. On the other hand, it decreases competition on the supply side (Bergemann and Bonatti (2011)) and improves ad space allocation (Athey and Gans (2010)). Bergemann and Morris (2016) organize the different effects of information disclosure scattered in the literature into the Individual Choice effect, whereby more information benefits each individual due to the "experiment" value of information (Blackwell (1953)), and the Strategic effect, whereby more information restricts the set of outcomes attainable in equilibrium.

My work differs from the theory of centralized matching in that it generally assumes that agents know their true preferences over potential partners prior to engaging in a match. Critically, the participants of decentralized matching markets have to inspect potential matches to identify the valuable ones. Papers that study centralized dynamic matching include Ashlagi *et al.* (2013); Akbarpour *et al.* (2016). They show that waiting to thicken improves matching in kidney exchange because individual agents do not fully incorporate the benefits of waiting. I emphasize the "reversed" effect: individual sellers wait too long because they do not fully incorporate the buyer loss form rejections (or buyer costs of waiting).

The paper contributes to the old economic question of the planner/intermediary's span of control. Optimality of strategic information disclosure policies, such as information coarsening, imply more control is optimal. In the context of platforms, Hagiu and Wright (2015) approach this question from delegation point of view, and the answer depends on who, the platform or sellers, engages in complimentary activities, such as marketing and advertising.

There is extensive operations research literature on staffing and queuing problems for platforms. The most related papers, however, explore the availability-driven coordination friction and price incentive schemes (Arnosti *et al.* (2014); Gurvich *et al.* (2015); Banerjee *et al.* (2015); Taylor (2016)).

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 this and other assumptions on the matching process 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.

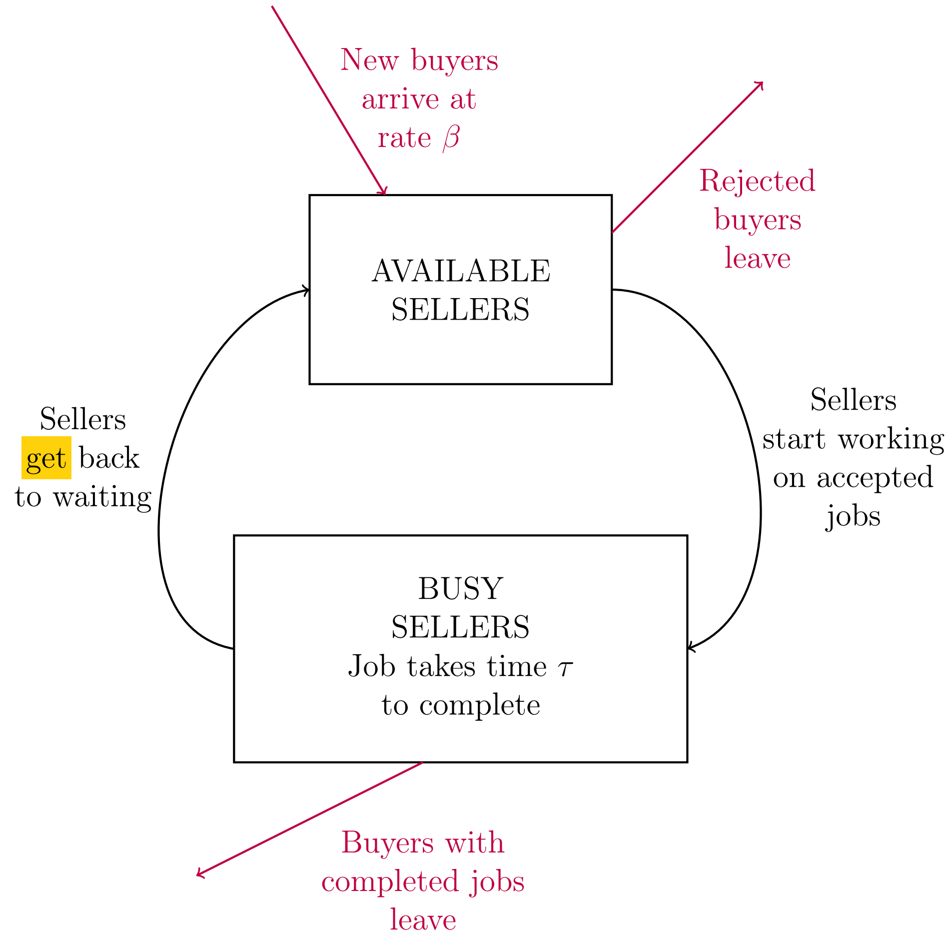
Buyer and seller preference heterogeneity. There are two dimensions of heterogeneity in the market. First, each seller has heterogeneous match payoff across buyers. Second, different sellers have different payoff functions over jobs. Concerning the platform's information disclosure problem, I need the following pieces of notation. Let x be buyer type, with the interpretation that x is buyer characteristics <u>observed</u> by the platform.[2] 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 <u>unobserved</u> by the platform.[3] 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:

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

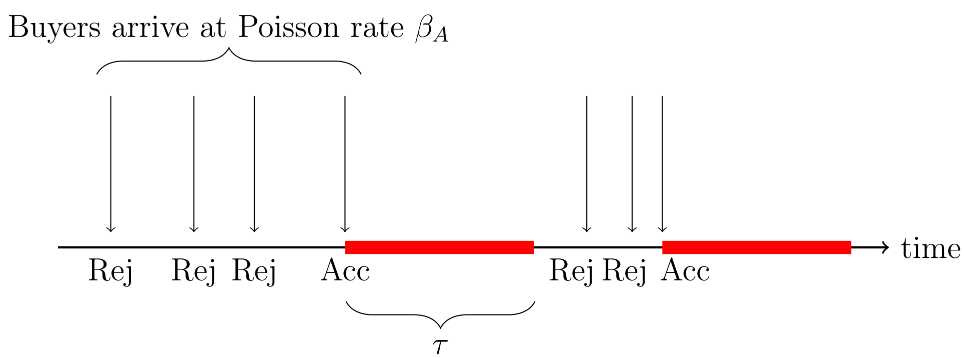
Platform: Information intermediation. Before the matching process starts running, the platform designs and commits to a disclosure policy that governs how buyer characteristics are disclosed to sellers. The platform observes buyer type x and sends a signal about x to the seller. The seller does not receive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

[2] 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.

[3] 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.[4] 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 $S' \subset S$.[5] 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:

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

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 become busy is equal to the flow of sellers who become available. The available-to-busy flow is equal to the buyer flow type-y sellers receive times their acceptance rate. Since buyers distribute uniformly across the available sellers, the

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

[5]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.

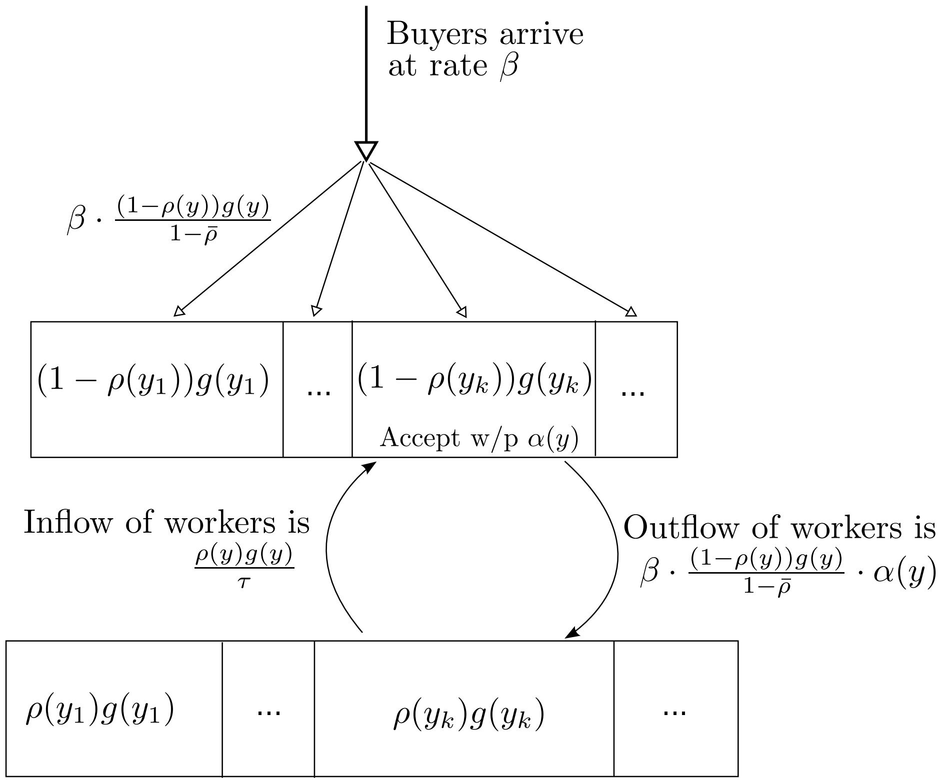


Figure 2: Matching process in a steady state. $g(y)$ is the mass of y-sellers, $\rho(y)$ is utilization rate, $\bar{\rho}$ is the average utilization rate.

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 available-to-busy flow is $\beta\frac{(1-\rho(y))g(y)}{1-\bar{\rho}}\alpha(y)$. The busy-to-available flow 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. See Figure 2 for the illustration. In a steady state, available-to-busy flow of sellers is equal to the busy-to-available flow:

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

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.[6] 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)[7]. Let $v(s, y)$ be the value of a new job with signal s, where 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: $V(y) = \beta_A \mathbb{E}[v(s, y)]$.[8] Put together, the seller optimization problem is given by:

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

[6] 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.

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

[8] 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 $\tau_r = \frac{1-e^{-r\tau}}{r}$.

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.

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 40.

2.4 Discussion of the modeling assumptions

In this subsection I discuss in detail the important assumptions of my model.

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%.

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 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 (see footnote 1). 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.

3 Market Design: Information Disclosure Policy

This section studies how the platform's information disclosure policy affects the equilibrium market outcome. I consider the general platform's objective of maximizing the weighted average of buyer and seller surplus, which includes as special cases the welfare maximization, profit maximization and maximizing the number of matches. I show the the full disclosure produces the sub-optimal market outcome because information disclosure aggravates sellers' cream-skimming behavior. I start with the benchmark case of identical seller, and then move on to the more general case of vertically differentiated sellers. In the latter, the optimal disclosure policy depends non-trivially on the shape of seller distribution, buyer arrival rate and seller capacity constraints.

3.1 Full disclosure: Seller coordination failure

This subsection establishes that the full disclosure leads to a Pareto sub-optimal market outcome. The reason behind it is the sellers' coordination failure. The inefficiency arises due to sellers' decentralized decision-making and capacity constraints.

To state the results of this and the next sections, I need to define Pareto-optimality in my setting. The market outcome $O = (V(\cdot), BS)$ is a combination of seller profits and consumer surplus. I say that a market outcome is *feasible* if there is a seller strategy profile that generates it, and $V(y) \geqslant 0$ for all y. A feasible outcome O is Pareto-optimal if there is no other feasible O' such that $V(y)' \geqslant V(y)$ for all y, and $BS' \geqslant BS$, and at least one seller type or buyers are strictly better off. The Pareto frontier is the set of all Pareto-optimal outcomes. Market outcome O is *implementable* if there is a disclosure policy such that the equilibrium outcome is O. The welfare is the sum of consumer surplus and joint seller profits. A market outcome is *efficient* if there is no other feasible outcome with higher welfare.

Write $V^\sigma(y)$, $\alpha^\sigma(y)$, BS^σ for steady-state profits, acceptance rates and consumer surplus when strategy profile σ is played. Imagine the platform starts with the full disclosure as its default disclosure policy. The next proposition shows that there is a strategy profile under which sellers are strictly better off than in the full disclosure equilibrium, they complete more jobs, and additionally, the buyers are also better off. The result implies that in decentralized matching markets, sellers face a a coordination problem.

Proposition 2. *Let σ^{FD} be the equilibrium strategy profile under full disclosure. Then there exists $\tilde{\sigma}$ such that for all y:*

$$\begin{aligned} \tilde{V}(y) &> V^{FD}(y), \\ \widetilde{BS} &> BS^{FD}, \\ \tilde{\alpha}(y) &> \alpha^{FD}(y). \end{aligned}$$

The full proof is in the Appendix on page 42. A very high-level intuition for the coordination problem is the following. A seller keeps his schedule open by rejecting low-value jobs to increase his individual chances of getting high-value jobs. As a result, in equilibrium, 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 call this behavior *cream-skimming*.

Here I give the proof sketch for the case of identical sellers, which gives further insights into the nature of the seller coordination problem. Under the full disclosure, seller profit V^{FD} is strictly positive because sellers accept only profitable jobs. The opportunity cost of accepting equals τV^{FD}, and so it is also strictly positive. In equilibrium, the jobs that are accepted have profits $\pi(x) \geqslant \tau V^{FD}$ (see Eq. (4)). However, the profitable jobs are those with $\pi(x) \geqslant 0$. Hence, some profitable jobs are rejected. Consider strategy $\tilde{\sigma}$ that maximizes the joint seller profits. It prescribes every seller to accept jobs with $\pi(x) \geqslant 0$. . Naturally, $\tilde{\sigma}$ yields $\tilde{V} > V^{FD}$. Acceptance rate is also higher, $\tilde{\alpha} > \alpha^{FD}$. Consumers are better off because consumer surplus is increasing in the acceptance rate.

Interestingly, unlike price competition that benefits buyers and improves market efficiency, seller competition for better buyers hurts buyers and decreases market efficiency.

Thus, cream-skimming is a market failure. I attribute the source of the 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 key necessary conditions for the cream-skimming externality to arise is forward-looking and capacity constrained sellers.

The fundamental reason behind the coordination failure is that collectively, the sellers are not capacity constrained (in time) while individually, the sellers *are* capacity constrained. When an individual seller accepts a job, he is off the market for time τ and cannot accept new jobs. He is afraid to miss valuable future jobs and therefore rejects low-value jobs. However, there are always some available sellers in the market, and it is feasible to accept all profitable jobs. Mathematically, the distinction between individual and collective capacity constraints is captured by having a continuum of sellers, so that while buyer traffic to each individual seller is stochastic, the aggregate buyer traffic is deterministic.

Proposition 2 shows that the full disclosure equilibrium is Pareto dominated by some strategy profile $\tilde{\sigma}$. Is there an information disclosure policy that induces $\tilde{\sigma}$? In the next section we give the affirmative answer to this question in the case of identical workers. The situation with heterogeneous sellers is more tricky, and we study it in Section 3.4.

3.2 Benchmark: Optimal information disclosure with identical sellers

I start by considering the case of identical sellers, i.e. Y is a singleton. The next proposition establishes that any Pareto optimal outcome (in profit-surplus space) is implementable by a disclosure policy.

Proposition 3. *Suppose the sellers are identical. Then for any Pareto optimal outcome* (V, BS) *there is a disclosure policy that implements it. Furthermore, an optimal disclosure* *policy has binary structure.*

The proof relies on the Revelation principle. Since there is one seller type and two actions, it is sufficient to consider only disclosure policies that send two signals, where a signal is "action recommendation". With such a binary signaling structure, the seller dynamic optimization problem reduces to the static optimization problem. Indeed, since there is only one signal with recommendation to accept, there is only one type of acceptable jobs. All profitable jobs are the same and there is no return to cream-skimming them. Since a Pareto optimal outcome is feasible with $V \geqslant 0$, sellers have incentives to follow the platform's recommendations to accept. For the details of the proof, see the Appendix.

Proposition 3 characterizes at once the range of possible objective functions. Indeed, any point on the Pareto frontier maximizes $\gamma V + (1-\gamma)BS$ for some $\gamma \in [0,1]$. The welfare maximization policy corresponds to $\gamma = 1/2$, and so the first-best efficient outcome is implementable by a disclosure policy. Figure 3 illustrates the result. Note that by Proposition 2 the full disclosure equilibrium outcome lies below the Pareto frontier.

Proposition 3 is related to the result of Bergemann *et al.* (2015) who show that segmentation of a monopolistic market can achieve every feasible combination of consumer and producer surplus. Their segmentation problem is a static signaling game with single receiver (monopolist), who also sets price, while my model is a signaling game with dynamically optimizing receivers, whose prices are fixed.

3.3 Three effects of information disclosure

Disclosure of buyer characteristics to sellers has three competing effects on welfare. The stronger effect determines the form and coarseness of the optimal disclosure.

The first effect is the standard *Individual Choice effect* on the seller side. From an individual seller's point of view, more information increases his set of attainable payoffs (Blackwell (1953)). Therefore, holding fixed the other sellers' behavior, he individually benefits from more information about buyers. Formally,

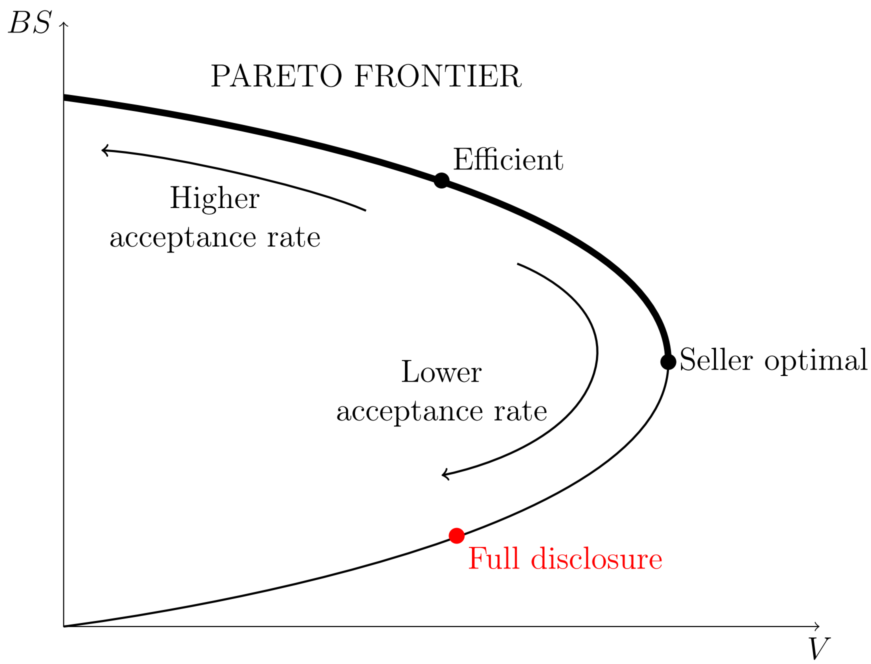


Figure 3: Graphical illustration of the set of feasible and implementable market outcomes in the case of identical workers. BS stands for buyer surplus, V stands for seller surplus. Disclosure policy can implement any point on the Pareto frontier (thick solid line). The full disclosure outcome is suboptimal.

Claim 1 (Seller Individual Choice effect). Fix β_A in the seller optimization problem (4). Let λ' be coarser than λ''. Then the profits $V' \leqslant V''$.

The second effect of information disclosure is the *Buyer-side effect*. More information available to sellers reduces the platform's ability to induce sellers to accept buyer-valuable jobs. It results in lower buyer surplus. Formally,

Claim 2 (Buyer-side effect). Fix $\tau = 0$. Let λ'' be such that there is $s \in \operatorname{supp} \lambda''$ with $\pi(s) < 0$. Then there is λ' coarser than λ'' such that $BS' > BS''$.

The third effect is the *Seller Option Value effect*. More information available to sellers increases their ability to cream-skim jobs, and so creates the positive option value of rejecting. In equilibrium, it hurts seller surplus because it is not collectively optimal for sellers to reject profitable jobs. Formally,

Claim 3 (Seller Option Value effect). Fix β_A in the seller optimization problem (4). Let λ' be coarser than λ''. Then the option values of rejection $\tau V' \leqslant \tau V''$.

The Buyer-side and the Option Value effects give a motive to the platform to coarsen information, while the Individual Choice effect gives a motive to release information. The Buyer-side and the Option Value effects are the instances of the general principle that more information imposes more constraints on the designer and reduces the set of outcomes he can induce (Bergemann and Morris (2016)). What effect is stronger depends on the primitives of the economic environment.

With identical sellers, too many efficient jobs are rejected under the full disclosure. Denote the efficient disclosure policy by $\hat{\lambda}$ and the set of efficient matches by $\hat{X}_a := \{x \in X\colon \pi(x) + u(x) \geqslant 0\}$. Disclosure $\hat{\lambda}$ sends the recommendation "accept" for any jobs in $\hat{X}_a$ and recommendation "reject" for jobs in $X \backslash \hat{X}_a$. Under the full disclosure, the accepted jobs are $X_a^{FD} := \{x \in X\colon \pi(x) \geqslant \tau V^{FD}\}$. Clearly, X_a^{FD} is a proper subset of $\hat{X}_a$.

When sellers are identical, the Buyer-side and the Option Value effects win over the Individual Choice effect. Indeed, jobs $\{x\colon -u(x) \leqslant \pi(x) \leqslant 0\}$ are rejected because sellers fail to internalize the effect of their acceptance decisions on buyers. This is the Buyer-side effect. Jobs $\{x\colon 0 \leqslant \pi(x) \leqslant \tau V\}$ are rejected because sellers fail to internalize the cream-skimming externality they impose on each other. This is the Option Value effect. The Individual Choice effect is weak because the platform observes seller preferences and can finely control their surplus. Therefore, $\hat{\lambda}$ is coarse.

The next result gives comparative statics of the efficient disclosure policy with respect to buyer traffic β, seller capacity constraint τ and buyer cost of rejection. Interestingly, $\hat{\lambda}$ does not depend on β or τ (optimal disclosure for other γ have this property, too). This implies that the same $\hat{\lambda}$ would be optimal if seller were unconstrained ($\tau = 0$).

Corollary 1. *Suppose the sellers are identical. Efficient information disclosure policy $\hat{\lambda}$ is independent of the intensity of buyer traffic β and seller capacity constraints τ. When buyer cost of rejection is higher, $\hat{\lambda}$ prescribes pooling more of marginal unprofitable jobs with inframarginal profitable jobs.*

Independence of $\hat{\lambda}$ from β and τ obtains due to the binary structure of $\hat{\lambda}$. Arrival rate to available sellers β_A matters to sellers only to the extent that higher arrival rate magnifies the opportunity cost of accepting. With binary $\hat{\lambda}$, the opportunity cost of accepting a profitable job is zero because all profitable jobs are the same.

The next section shows that with heterogeneous sellers, the Individual Choice Effect can be the strongest. Moreover, the optimal disclosure policy depends on β and τ.

3.4 Optimal information disclosure with heterogeneous sellers

This section studies the information disclosure problem with heterogeneous sellers in the linear payoff environment. It is a leading case of my analysis because in most marketplaces, the intermediary observes seller preferences imperfectly. I characterize the optimal disclosure policy and show that it is qualitatively different from the statically optimal disclosure found in the prior literature. Moreover, unlike with identical sellers, the Pareto frontier is generally not attainable. Finally, under certain conditions, which I provide, the full disclosure is the only optimal policy.

With heterogeneous sellers, the Individual Choice effect is stronger. To see why, imagine there are two types of sellers: professionals and amateurs. Professionals can profitably complete a larger set of jobs than amateurs. The platform does not observe seller type. When the platform designs the disclosure policy, it should take into account that the same disclosure policy has different impacts on professionals and on amateurs. Amateurs can profitably complete only a small subset of jobs, and so they need finer disclosure to tell apart profitable jobs from unprofitable ones. If the disclosure is too coarse, amateurs reject all jobs. Professionals have a large set of profitable jobs, and so their average profit per job is high. Pooling more unprofitable marginal jobs with profitable inframarginal jobs keeps professionals' average profits positive but induces higher acceptance rate. Whether it is optimal to coarsen the information disclosure or not thus depends on the relative population sizes of amateurs and professionals. If there are more professionals than amateurs, then coarser disclosure is optimal: it increases the total acceptance rates even though amateurs stop working. If there are more amateurs, finer disclosure is optimal. In the rest of this section I rigorously study this problem for the general continuous distribution of seller types.

Consider the setting that I call the *linear payoff* environment. The space of buyer types is $X = [0, 1]$, with the interpretation that x is the difficulty of the job. The space of seller types is $Y = [0, \overline{y}]$, $\overline{y} \geqslant 1$, with the interpretation that y is the seller skill level. The seller profit function is $\pi(x, y) = y - x$. High-y sellers are "professionals", and the low-y sellers are "amateurs". Buyer match value is $u(x, y) = u$. Impose the regularity condition necessary for the results below: $f(0) > 0$.

The platform's objective is maximizing the weighted average of buyer surplus and joint seller profits.

$$\mathcal{J}(\gamma) = \gamma BS + (1 - \gamma)V,$$

where $V = \int_Y V(y)dG(y)$ is the joint seller profits, and $BS = u \cdot M$ is buyer surplus, where M is the total number of matches formed over unit of time. The general objective $\mathcal{J}(\gamma)$ includes as special cases welfare maximization ($\gamma = 1/2$), seller profits maximization ($\gamma = 0$) and maximization of the number of matches ($\gamma = 1$).

The next proposition is the second main result of the paper. It characterizes the disclosure policy that maximizes $\mathcal{J}(\gamma)$ for the case of uniform seller type distribution.

Definition. Disclosure λ is x^**-upper-coarsening* for some $x^* \in [0, 1]$ if λ fully reveals $x < x^*$ and pools all $x > x^*$.[9]

Proposition 4. *Suppose $G = U[0, \overline{y}]$, $\overline{y} \geqslant 1$. Then for any $\gamma \in [0, 1]$, there is unique $x^*_\gamma \in [0, 1]$ such that x^*_γ-upper-coarsening maximizes $\mathcal{J}(\gamma)$. Furthermore, x^*_γ is decreasing in γ.*

- *For any $\gamma \in [0, 1]$, there exist $\beta\tau$ and $\overline{y}$ large enough such that $x^*_\gamma < 1$ (some coarsening is strictly optimal).*

- *If $0 < \beta\tau < 1/2$, then $x^*_\gamma = 1$ for any γ (full disclosure is strictly optimal).*

[9] The terminology is borrowed from Kolotilin *et al.* (2015).

I reserve notation x^*_γ to denote the cutoff in the upper-coarsening disclosure policy that maximizes $\mathcal{J}(\gamma)$. This way, x^*_0, x^*_1 and $x^*_{1/2}$ are the highest truthfully revealed buyer types under profits-maximizing disclosure, match-maximizing disclosure and the efficient disclosure, respectively.

First, Proposition 4 shows that the optimal disclosure involves pooling hard tasks and truthfully revealing easy tasks. As we will see in the discussion below, the reason behind this form of disclosure is to reduce of the professionals' opportunity cost of accepting.

Second, when the platform puts more weight on buyer surplus, the optimal disclosure policy is coarser. In particular the match-maximizing disclosure is coarser than the efficient disclosure that in turn, is coarser than the profits-maximizing disclosure ($x^*_0 \geqslant x^*_{1/2} \geqslant x^*_1$).

Third, Proposition 4 shows that the optimal disclosure policy in the case of the uniform distribution of seller types depends on the intensity of buyer traffic β, tightness of seller capacity constraints τ and the spread of seller types $\overline{y}$. If $\beta\tau$ is large enough and there are sufficiently high seller types, then upper-coarsening is optimal. Conversely, if buyer traffic is low or capacity constraints are loose, full disclosure is strictly optimal.

I am going to contrast the optimal disclosure policy found in Proposition 4 to the solution of the static disclosure problem. The *static disclosure problem* is the one shot interaction between the platform and the sellers. My model reduces to the static disclosure problem when $\tau = 0$. Indeed, when $\tau = 0$, sellers are always available and act myopically. The static disclosure problem has been extensively studied in the prior literature.

The upper-coarsening form of the optimal policy is qualitatively different from the solution to the static disclosure policy in the same environment. The relevant result from the prior literature is as follows.

Fact 1. *Suppose $\tau = 0$ and consider the platform's objective of maximizing the number of matches ($\gamma = 1$).*

- *If g is decreasing, then the full disclosure is optimal;*

- *If g is increasing, then the no disclosure is optimal;*

- *If g is constant, then any disclosure is optimal.*

The result appears e.g. in Kolotilin *et al.* (2015), and the implied concavification reasoning goes back to Aumann *et al.* (1995) and Kamenica and Gentzkow (2011). The proof of Fact 1 follows from Corollary 4 in the next section.

In the static disclosure problem, if the distribution of seller types is uniform, the information disclosure does not affect the number of matches. Any coarsening of the full disclosure policy decreases the acceptance rate of lower-type sellers and increases the acceptance rate of high-type sellers. When distribution of seller types is uniform, these two forces cancel out and the total number of matches is unchanged.

In contrast, in dynamic setting, Proposition 4 shows that information disclosure does affect the number of matches. In particular, the upper-coarsening is strictly optimal. The additional affects that arise when $\tau > 0$ are the Option Value effect and the availability effect.

To better see what forces make the upper-coarsening optimal, consider the following two simplifications of the model. Each simplification alters a part of the original model. Recall that the model has two main components: the matching system, call it $\mathcal{M}$, and the seller optimization problem, call it $\mathcal{O}$. The first simplification keeps $\mathcal{O}$ in its exact form as in (4) but has the alternative matching system $\mathcal{M}'$ that replenishes any available seller immediately after he becomes busy with a new seller of the same type. In $(\mathcal{O}, \mathcal{M}')$, the mass of available sellers is always 1, and the distribution is always G. The second simplification keeps $\mathcal{M}$ but has the alternative $\mathcal{O}'$ in which sellers act myopically. In $(\mathcal{O}', \mathcal{M})$, the seller accept all profitable jobs but it sill takes time τ to complete them.

Corollary 2. *Suppose the distribution of available seller types is exogenous $G = U[0,1]$ (simplification $(\mathcal{O}, \mathcal{M}')$). Then only the no disclosure policy maximizes the number of matches.*

The result demonstrates the workings of the Option Value effect in the case of heterogeneous sellers. Under the premises of Corollary 2, the Option Value effect completely dominates the Individual Choice effect. Compare the no disclosure to the full disclosure. If seller were myopic, then by Fact 1 coarsening does not affect the number of matches. However, with forward-looking sellers, there is a difference. The coarsening of information increases the acceptance rate of professionals unproportionally because it decreases their option value of rejection. As a result, the no disclosure is optimal.

Corollary 3. *Suppose $G = U[0,1]$. If sellers are myopic (simplification $(\mathcal{O}', \mathcal{M})$), then full disclosure is strictly optimal to maximize the matching rate.*

In this result, I shut down the Option Value effect and instead focus on the effect of endogenous distribution of seller types. In the equilibrium, the pdf of available seller types is decreasing because high seller types have higher acceptance rates and so are less available. Results from the static disclosure (Fact 1) suggest that in this case the full disclosure must be optimal. Corollary Corollary 3 confirms that this is indeed the case.

In the original model $(\mathcal{O}, \mathcal{M})$ both effects from Corollary 2 and Corollary 3 are present. The resulting optimal policy is a partial coarsening. In the case of uniform G, as Proposition 4 shows, it is upper-coarsening.

For general G, the shape of the optimal disclosure can be quite arbitrary even in the static case. The heuristic is to pool x on the increasing part of pdf g, and reveal x on the decreasing part of g. With forward-looking agents, it gets even less tractable. Nevertheless, I give the first order condition in Lemma 3 that can be used to analyze the general case.

Profit maximization may also require coarse disclosure policy. Proposition 4 shows that when $\gamma = 0$, the non-trivial upper-coarsening can be optimal ($x_0^* < 1$). The coarsening is necessary to alleviate the seller coordination problem when $\beta\tau$ is large. Large $\beta\tau$ implies large option value of rejecting, and the option value is the largest for professionals. Large x are the professionals' marginal buyers. Therefore coarsening at the right end of X decreases the professionals' return to rejecting and increases the fraction of accepted profitable jobs. This improves profits.

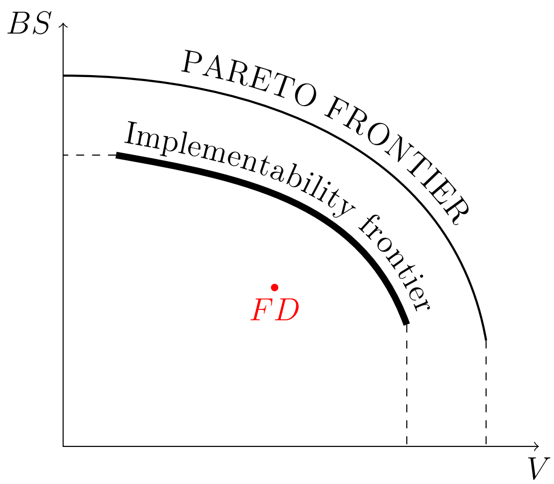
Figure 4 illustrates Proposition 4 and contrasts it with the case of identical sellers. From Proposition 2 we know that the full disclosure outcome is suboptimal. In the case of identical sellers, it was possible to implement any point on the Pareto frontier by information disclosure (Proposition 3), and therefore coarsening was necessary for optimality. In the case of heterogeneous sellers, the Pareto frontier is not implementable in the generic case because sellers have private information. Therefore, the "implementability frontier" in Figure 4 is below the Pareto frontier. Further, if $\beta\tau$ and $\overline{y}$ are large enough then the full disclosure outcome is below the implementability frontier, and efficiency requires some coarsening. The optimal disclosures in this case are described in Proposition 4. If $\beta\tau$ is small, the implementability frontier consists of only the full disclosure outcome. That is, the full disclosure is optimal for welfare maximization, match-rate maximization or joint profits maximization.

3.5 Main lemma and proof outline of Proposition 4

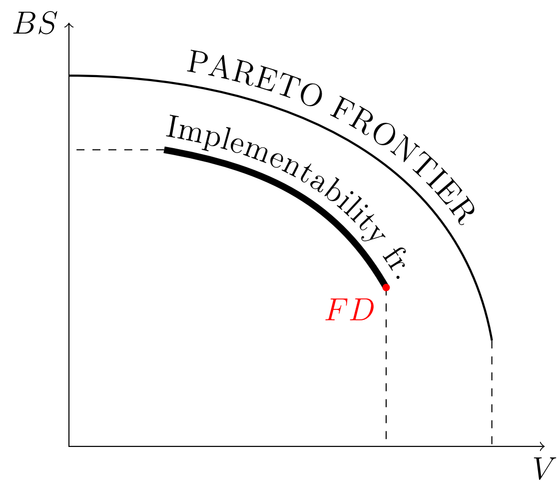
In this subsection I sketch the proof of Proposition 4. The main idea behind the proof is to represent information disclosure λ as some bounded convex function $\Lambda(\cdot)$, and then use the calculus of variations to find the optimal Λ. The main technical result of the paper is Lemma 3.

The proof of Proposition 4 relies on a sequence of four lemmas. Lemma 1 establishes the one-to-one correspondence between information disclosure policies and convex functions from some set. Lemma 2 finds the convenient representation of the seller dynamic optimization problem. Lemma 3 finds a variational derivative of the platform's objective $\mathcal{J}$. Lemma 4 provides a necessary condition for optimality of a disclosure policy.

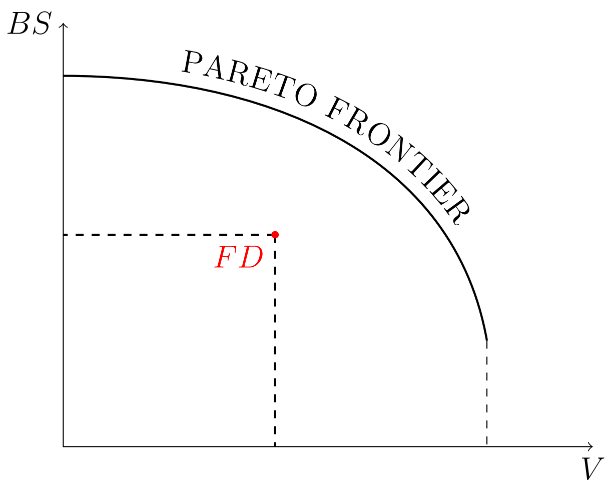
Denote the posterior mean of x conditional on signal s by $z(s) := \int_X x\, ds(x)$. I reserve notation z for a typical posterior mean of x. Denote by F^λ the distribution of $z(s)$ when the platform uses disclosure policy λ. We have $F^\lambda(\zeta) = \lambda\{z(s) \leqslant \zeta\}$. Define the *option value*



(a) $\beta\tau$ is large enough and $\overline{y}$ is large enough. The full disclosure is neither efficient, nor profits-maximizing, nor #matches-maximizing.



(b) The full disclosure is profits-maximizing but not efficient.



(c) $\beta\tau \in (0, 1/2)$. The implementability frontier is degenerate and consists of only the full-disclosure outcome.

Figure 4: Graphical illustration of the set of feasible market outcomes and the limits of implementability using information design in the case of heterogeneous workers in the linear payoff environment with the uniform seller type distribution. BS stands for buyer surplus, V stands for seller surplus. FD stands for the full-disclosure outcome.

function $\Lambda\colon [0,\infty) \to \mathbb{R}_+$:

$$\Lambda(z;\lambda) := \int_0^z F^\lambda(\zeta)\, d\zeta. \tag{6}$$

As we will see from the Lemma 2, $\Lambda(z)$ is proportional to the option value of rejecting a job with expected difficulty z. Let $\overline{\Lambda}$ be the option value function under full disclosure, $\overline{\Lambda}(z) := \int_0^z F(\zeta)\, d\zeta$. Similarly, let $\underline{\Lambda}$ be the option value function under no disclosure, $\underline{\Lambda}(z) := \max\{0, z - \mathbb{E}[x]\}$. Let

$$\mathcal{L} := \left\{\Lambda(z)\colon \Lambda(z) \text{ is increasing, convex and pointwise between } \overline{\Lambda}(z) \text{ and } \underline{\Lambda}(z)\right\}.$$

The next lemma establishes a one-to-one correspondence between functions from $\mathcal{L}$ and option value functions defined in (6).

Lemma 1. *$\ell \in \mathcal{L}$ if and only if there is $\lambda \in \Delta(S)$ such that $\Lambda(\cdot,\lambda) = \ell$.*

The power of Lemma 1 is that it shows that any disclosure policy can be represented as some non-negative, non-decreasing and convex function from $\mathcal{L}$. See Figure 5 for illustration. I am going to use notation Λ for a typical element of $\mathcal{L}$. The optimization of $\mathcal{J}$ with respect to $\lambda \in \Delta(S)$ is equivalent to the optimization with respect to $\Lambda \in \mathcal{L}$. The latter allows me to use the calculus of variations to find the optimality condition below.

The next lemma characterizes the optimal seller strategy and demonstrates that the seller optimization problem depends on λ only through Λ.

Lemma 2. *For any disclosure policy λ, seller's optimal strategy has a cutoff form with cutoff $\hat{z}(y)$ such that y-seller accepts all jobs with expected difficulty $z < \hat{z}(y)$ and rejects all jobs with $z > \hat{z}(y)$. Furthermore, for any β_A, seller payoff $V(y)$ and cutoff $\hat{z}(y)$ are solutions to the following system of equations:*

$$V(y) = \frac{y - \hat{z}(y)}{\tau} = \beta_A \Lambda(\hat{z}(y)). \tag{7}$$

The lemma implies that the platform's objective $\mathcal{J}$ depends on λ only through Λ. It is

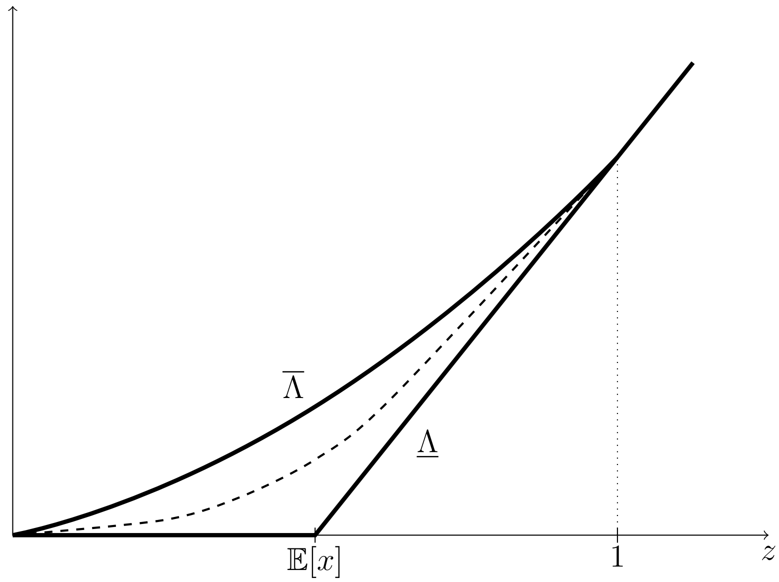


Figure 5: Any disclosure policy λ can be represented as an increasing, convex function Λ point-wise between $\underline{\Lambda}$ and $\overline{\Lambda}$.

used in the next lemma, which is the main technical result of the paper.

Consider functional $\mathcal{I}(\Lambda)\colon \mathcal{L} \to \mathbb{R}$ and consider variation $\delta\Lambda(y)$. The first variation of $\mathcal{I}$ is $\delta\mathcal{I} = \mathcal{I}(\Lambda + \delta\Lambda) - \mathcal{I}(\Lambda)$. The variational derivative of $\mathcal{I}$ with respect to Λ is function $\phi(y)$ such that $\delta\mathcal{I} = \int \phi(y)\delta\Lambda(y)dy + o(\delta\Lambda)$ as $\delta\Lambda \rightrightarrows 0$. If the variational derivative exists, it is denoted by $\delta\mathcal{I}/\delta\Lambda$.

Denote by $\nu(y) := 1 - \rho(y)$ the fraction of type-y sellers who are available.

Lemma 3 (Main Lemma)**.** *For any initial $\Lambda \in \mathcal{L}$, the variational derivative of the flow of matches M with respect to Λ exists and equals:*

$$\frac{\delta M}{\delta \Lambda} = K_1 \cdot \left[g(y)\nu'(y) - (g(y)\nu^2(y))'\right], \tag{8}$$

where $K_1 = \beta / \int \left[\nu^2(y) - \tau V(y)\nu'(y)\right] dG(y) > 0$. Similarly, the variational derivative of the joint profits V with respect to Λ exists and equals:

$$\frac{\delta V}{\delta \Lambda} = \frac{\delta M}{\delta \Lambda} \cdot K_2 + \nu(y)\beta_A,$$

where $K_2 = \tau \int \nu(y)V(y)dG(y)/\bar{\nu} > 0$.

To see the contribution of Lemma 3, compare it to the static disclosure problem.

Corollary 4. *Suppose* $\tau = 0$. *Then*

$$\frac{\delta M}{\delta \Lambda} = -\beta g'(y). \tag{9}$$

If g is decreasing, then the full disclosure is optimal. If g is increasing, then the no disclosure is optimal.

The result easily follows from Lemma 3 using the fact that when $\tau = 0$, $\nu(y) = (1 + \tau\beta_A\alpha(y))^{-1} = 1$. When sellers are capacity constrained ($\tau = 0$), the original formula (9) has to be adjusted, as shown in (8).

I now explain the additional terms in (8) in more detail. Consider uniform distribution of seller types, $G = U[0,1]$. By (8),

$$\frac{\delta M}{\delta \Lambda} \propto -(\nu^2(y) - \nu(y))'. \tag{10}$$

When $\tau = 0$, it reduces to

$$\frac{\delta M}{\delta \Lambda} = 0.$$

Therefore, the disclosure has no effect on the number of matches in the static case but does have effect in the dynamic case.

Term $-\nu(y)$ in (10) corresponds to the Individual Choice effect. The Individual Choice effect arises because sellers do not act myopically and reject low-value jobs due to dynamic optimization. High types have greater option value of rejecting a job (see Eq. (4)), and so coarsening information has additional effect on acceptance by decreasing the sellers' option value of rejection. By Corollary 4, $-\nu(y)$ acts as a density function, and since $\nu(y)$ is decreasing, this creates a motive for the intermediary to use coarser disclosure policy.

Term $\nu^2(y)$ in (10) corresponds to the availability effect. The availability effect arises because in equilibrium, high types are less available than low types. Therefore, the pdf of available seller types is decreasing. By Corollary 4, $\nu^2(y)$ acts as a density function, and since $\nu(y)$ is decreasing, this creates a motive for the intermediary to use finer disclosure policy.

The next lemma provides a necessary condition for optimality of a disclosure policy.

Lemma 4. *If λ_0 maximizes $\mathcal{J}$, and $\delta\mathcal{J}/\delta\Lambda$ evaluated at λ_0 crosses zero from above at most once, then λ_0 is upper-coarsening.*

Now I sketch the key steps of the proof of the main result for the case of heterogeneous seller Proposition 4. The complete proof relies on more technical lemmas and is deferred to the Appendix on page 45.

Proof sketch of Proposition 4. By Lemma 3,

$$\begin{aligned}\frac{\delta\mathcal{J}}{\delta\Lambda} &= \gamma u\frac{\delta M}{\delta\Lambda} + (1-\gamma)\left(\frac{\delta M}{\delta\Lambda}K_2 + \nu(y)\beta_A\right) = \\ &= (\gamma u + K_2(1-\gamma))\frac{\delta M}{\delta\Lambda} + (1-\gamma)\beta_A\nu(y), \end{aligned} \tag{11}$$

where $K_2 > 0$. Evaluating with $G = U[0,\overline{y}]$,

$$\frac{\delta M}{\delta\Lambda} = K_1\overline{y}^{-1}(\nu(y) - \nu^2(y))' = K_1\overline{y}^{-1}(1-2\nu(y))\nu'(y), \tag{12}$$

where $K_1 > 0$. Since $\nu(0) = 1$ and $\nu(y)$ is non-negative and decreasing, $\delta\mathcal{J}/\delta\Lambda$ is either positive for all $y \in [0,\overline{y}]$ or crosses zero once from above. Denote by λ^*_γ the disclosure policy that maximizes $\mathcal{J}(\gamma)$. By Lemma 4, λ^*_γ is upper-coarsening.

To see that the cutoff x^*_γ is decreasing in γ, note that larger γ puts more weight on the positive term $\beta_A\nu(y)$ in (11). Therefore the region of Y with negative $\delta\mathcal{J}/\delta\Lambda$ is smaller.

Whether $x^*_\gamma = 1$ or strictly less than 1 depends on the existence of $y \leqslant \overline{y}$ with $\nu(y) < 1/2$. Indeed, from (12), if $\nu(y) > 1/2$ for all $y \leqslant \overline{y}$, then $\delta\mathcal{J}/\delta\Lambda \geqslant 0$ for all y. For the details, refer to the proof in the Appendix on page 45. □

4 Appendix

A Lemmas

Lemma 5. *Fix the arbitrary increasing $\alpha(y) \in [0,1]$, $y \in Y$.*

- *Average utilization rate $\bar{\rho} \in [0,1]$ is a solution to*

$$1 = \int \frac{dG(y)}{1 - \bar{\rho} + \beta\tau\alpha(y)}. \tag{13}$$

- *The solution $\bar{\rho}$ exists, is unique, increases in $\alpha(y)$ for any $y \in Y$, in β and in τ.*

- *Utilization rate of type y $\rho(y)$ increases in $\alpha(y')$ for any $y' \in Y$.*

Proof. Find from (2) that

$$1 - \rho(y) = \frac{1}{1 + \tau\beta\alpha(y)/(1-\bar{\rho})}. \tag{14}$$

Take the integral using cdf $G(y)$ to obtain $1 - \bar{\rho} = \int dG(y)/(1 + \tau\beta\alpha(y)/(1-\bar{\rho}))$. Rearrange and get (13). The right-hand side of (13) is increasing in $\bar{\rho}$. Evaluated with $\bar{\rho} = 0$, it equals $\int \frac{dG(y)}{1+\beta\tau\alpha(y)} \leqslant 1$. Evaluated with $\bar{\rho} = 1$, it equals $\int \frac{dG(y)}{\beta\tau\alpha(y)} \geqslant 1$, using Assumption Assumption 4. Therefore, the solutions exists and is unique. Monotonicity of $\bar{\rho}$ is straightforward.

Finally, if $\alpha(y')$ increases (at the neighborhood of y'), $\bar{\rho}$ increases. Therefore, the right hand side of (14) decreases. Therefore, $\rho(y)$ increases. □

Lemma 6. *In the steady state,*

$$\beta \leqslant \beta_A \leqslant \frac{\beta}{1 - \tau\beta}.$$

Proof. From (3), $\beta_A = \beta/(1-\bar{\rho})$. Therefore, $\beta_A \geqslant \beta$.

Find from (2) that $\tau\beta\frac{1-\rho(y)}{1-\bar{\rho}}\alpha(y) = \rho(y)$. Take expectation wrt y and obtain $\bar{\rho} = \tau\beta \int \frac{1-\rho(y)}{1-\bar{\rho}}\alpha(y)dG(y) \leqslant \tau\beta \int \frac{1-\rho(y)}{1-\bar{\rho}}dG(y) = \tau\beta$. Therefore, $\beta_A \leqslant \frac{\beta}{1-\tau\beta}$. □

Lemma 7. *Assume the linear payoff environment. In the steady state equilibrium with disclosure policy λ, $\alpha(y) = \Lambda'(\hat{z}(y))$ for sellers of mass 1. Furthermore,*

- *$\alpha(y)$ is increasing in y.*
- *For any $\Lambda \in \mathcal{L}$, there is $\breve{y} > 0$ such that $\alpha(y) = 1$ for $y \geqslant \breve{y}$.*
- *Considering exogenous variations of $\beta_A \tau$ in the seller optimization problem (7), $\alpha(y)$ is decreasing in $\tau\beta_A$ for any $y \in Y$.*

Proof. By Lemma 2, the the accepted jobs are those with $z < \hat{z}(y)$. Using definition of Λ from (6), probability of accepting is

$$\lambda\{z(s) < \hat{z}(y)\} \leqslant \alpha(y) \leqslant \lambda\{z(s) \leqslant \hat{z}(y)\}$$
$$F^{\lambda}(\hat{z}(y)-) \leqslant \alpha(y) \leqslant F^{\lambda}(\hat{z}(y)+)$$
$$\Lambda'(\hat{z}(y)) \leqslant \alpha(y) \leqslant \Lambda'(\hat{z}(y))$$

Points of discontinuity of F^{λ} make a set of measure zero. Since seller types have full support on $[0, \overline{y}]$, $\alpha(y) = \Lambda'(\hat{z}(y))$ for sellers of mass 1.

From (7), $\hat{z}(y)$ is increasing in y. Since Λ is convex, $\alpha(y)$ is increasing in y.

Since $X = [0, 1]$, $\Lambda'(z) = 1$ for $z \geqslant 1$. And for y large enough, $\hat{z}(y) > 1$.

From (7), $\hat{z}(y)$ is decreasing in $\tau\beta_A$ for any $y \in Y$. Since Λ is convex, $\alpha(y)$ is decreasing in $\tau\beta_A$. □

B Proofs of Propositions 1-3

Proof of Proposition 1. Step 1. Restricting set of strategies to cutoff strategies. Fix $y \in Y$. By (4) the optimal seller strategy is such that all $S_a(y) = \{s \colon \pi(s, y) > \tau V(y)\}$ are accepted, all $S_r(y) = \{s \colon \pi(s, y) < \tau V(y)\}$ are rejected, and the seller is indifferent between accepting and rejecting signals from $S_m(y) := \{s \colon \pi(s, y) = \tau V(y)\}$. Therefore any optimal strategy has the cutoff form:

$$\sigma(s,y) = \begin{cases} 1, & s \in S_a(y) \\ \in [0,1], & S_m(y) \\ 0, & s \in S_r(y) \end{cases}$$

Denote the cutoff for type-y seller by $\hat{\pi}(y) := \tau V(y)$. Using (4),

$$\begin{aligned} V(y) &= \beta_A \int (\pi(s,y) - \tau V(y))\sigma(s,y)\lambda(ds) \\ \hat{\pi}(y) &= \tau\beta_A \int (\pi(s,y) - \hat{\pi}(y))\sigma(s,y)\lambda(ds) \\ \hat{\pi}(y) &= \tau\beta_A \int (\pi(s,y) - \hat{\pi}(y))I\{\pi(s,y) > \hat{\pi}(y))\}\lambda(ds) \end{aligned} \tag{15}$$

Given λ and β_A, the cutoff of the optimal strategy is a solution to (15). The solution is unique because the left-hand side of (15) is strictly increasing in $\hat{\pi}(y)$ while the left hand side is decreasing in $\hat{\pi}(y)$.

Step 2. Existence. Consider a correspondence $\psi\colon [0,1] \rightrightarrows [0,1]$, which maps $\bar{\rho}$ to a set of "reaction" $\bar{\rho}$'s by the following procedure. To find $\psi(\bar{\rho})$, first find the unique cutoff function $\hat{\pi}$ from (15) using $\beta_A = \beta/(1-\bar{\rho})$. Cutoff $\hat{\pi}$ does not pin down the acceptance rates α uniquely because marginal signals from S_m can have positive probability under λ. The acceptance rates congruent with $\hat{\pi}(y)$ are integrable $\alpha(y)$ such that

$$\lambda(S_a(y)) \leqslant \alpha(y) \leqslant \lambda(S_a(y)) + \lambda(S_m(y)), \quad \forall y \in Y.$$

Take all α that are congruent with $\hat{\pi}$, call this set $\mathcal{A}$. For any $\alpha \in \mathcal{A}$, find $\bar{\rho}$ as shown in Lemma 5. Going over all $\mathcal{A}$ will produce the set of $\bar{\rho}$. This will be $\psi(\bar{\rho})$.

Clearly, $\mathcal{A}$ is convex. Thus, $\psi(\bar{\rho})$ is also convex. Since $\psi(\bar{\rho})$ is an interval subset of $[0,1]$, it is easy to see that $\psi(\bar{\rho})$ is also closed. ψ is upper hemi-continuous because $\hat{\pi}$ is continuous in β_A according to (15). Therefore, by Kakutani's theorem, ψ has a fixed point.

Step 3. Uniqueness. Suppose $\bar{\rho}^1$ and $\bar{\rho}^2$ are two distinct fixed points of ψ. Suppose

$\bar{\rho}^1 > \bar{\rho}^2$. Then $\beta_A^1 > \beta_A^2$. By (15) $\hat{\pi}^1(y) > \hat{\pi}^2(y)$ for any $y \in Y$. If so, then whenever $\pi(s,y) \geqslant \hat{\pi}^1(y)$ we also have $\pi(s,y) > \hat{\pi}^2(y)$. But this means that $S_a^2(y) \supseteq S_a^1(y) \cup S_m^1(y)$. Therefore $\alpha^2(y) \geqslant \lambda(S_a^2) \geqslant \lambda(S_a^1 \cup S_m^1) \geqslant \alpha^1(y)$ for all y. By Lemma 5, this implies $\bar{\rho}^2 \geqslant \bar{\rho}^1$. A contradiction.

We showed that there is a unique $\bar{\rho}$ that can arise in a steady-state equilibrium. By the argument below (15), the strategy cutoffs $\hat{\pi}(\cdot)$ are also pinned down uniquely in the steady-state equilibrium. □

Proof of Proposition 2. By (4),

$$
\begin{aligned}
V(y) &= \beta_A \int (\pi(s,y) - \tau V(y))\sigma(s,y)d\lambda(s) \\
V(y) &= \beta_A \nu(y) \int \pi(s,y)\sigma(s,y)d\lambda(s),
\end{aligned}
$$

where $\nu(y) = (1 + \tau\beta_A\alpha(y))^{-1}$. In a steady state, by (2), $\beta_A\nu(y) = \rho(y)/(\tau\alpha(y))$. Therefore,

$$
\begin{aligned}
V(y) = \frac{\int \pi(s,y)\sigma(s,y)d\lambda(s)}{\alpha(y)} \frac{\rho(y)}{\tau} &= \\
= \mathbb{E}[\pi(s,y) \mid \text{acc.}]\frac{\rho(y)}{\tau}.
\end{aligned}
$$

Now σ^{FD} prescribes that jobs $\{x \colon \pi(x,y) > \tau V(y)\}$ are accepted with probability 1. Consider an alternative strategy profile

$$
\tilde{\sigma}(x,y) = \begin{cases} 1, & \pi(x,y) > 0 \\ 0, & \pi(x,y) \leqslant 0 \end{cases}
$$

Since $V(y) > 0$, we have $\mathbb{E}[\pi(s,y) \mid \text{acc. with } \sigma^{FD}] < \mathbb{E}[\pi(s,y) \mid \text{acc. with } \tilde{\sigma}]$. Also, $\alpha^{FD}(y) < \tilde{\alpha}(y)$. Finally, by Lemma 5, $\rho^{FD}(y) < \tilde{\rho}(y)$. Therefore, $V^{FD}(y) < \tilde{V}(y)$. □

Proof of Proposition 3. Take any Pareto optimal pair $O = (V, CS)$. Since O is feasible, there is seller strategy profile σ that induces O. Since there is one seller type and two actions, it is sufficient to consider only the binary signaling structures (Revelation principle). A binary signaling structure has two signals, where a signal is "action recommendation". Let s_a be the recommendation to accept, and s_r be the recommendation to reject. Denote this signaling structure by $\hat{\lambda}$. We need to check the incentive constraints, that is, to make sure that the sellers would follow the recommendations of $\hat{\lambda}$.

From (4) we have that $v(s_a) = \pi(s_a) - \tau V$, $v(s_r) = 0$, and $V = \beta_A(\pi(s_a) - \tau V)\hat{\lambda}(s_a)$. The incentive constraints require that $\pi(s_a) \geqslant \tau V$ and $\pi(s_r) \leqslant 0$. For the former,

$$\tau V = \frac{\tau\beta_A\hat{\lambda}(s_a)}{1+\tau\beta_A\hat{\lambda}(s_a)}\pi(s_a) < \pi(s_a).$$

For the latter, recall that O is Pareto optimal, hence σ accepts all profitable jobs. This implies that

$$\pi(s_r) \leqslant 0 < \tau V.$$

□

C Proof of Proposition 4

The proof of Proposition 4 relies on a sequence of lemmas.

Lemma 8. *Suppose the linear payoff environment with $G = U[0, \overline{y}]$. For any (large) $L > 0$ there is $\beta\tau < 1$ large enough and $\breve{y}$ (large enough) such that if $\overline{y} \geqslant \breve{y}$, we have $\tau\beta_A \geqslant L$.*

Proof. Since $\beta_A = \beta/\bar{\nu}$, rewrite (13) as

$$\beta\tau = \int_0^{\overline{y}} \frac{dy/\overline{y}}{\frac{1}{\tau\beta_A} + \alpha(y; \tau\beta_A)}, \tag{16}$$

where I made explicit that α depends on $\tau\beta_A$ in equilibrium. Treat the right hand side of (16) as a function of $\tau\beta_A$ and $\overline{y}$ and denote it by $\psi(\tau\beta_A, \overline{y})$. First, ψ is strictly increasing in $\tau\beta_A$ because by Lemma 7 α is decreasing in $\tau\beta_A$. Second, ψ is decreasing in $\overline{y}$ because by

Lemma 7 α is increasing in y. Third, using the second part of Lemma 7 and uniformity of G, $\lim_{\overline{y}\to\infty}\psi = ((\tau\beta_A)^{-1}+1)^{-1} < 1$. Pick $\breve{y}$ such that $\psi(L,\breve{y}) < 1$. Let $(\beta\tau)^* := \psi(L,\breve{y})$. We have that $\beta_A\tau > L$ whenever $\beta\tau > (\beta\tau)^*$ or $y > \breve{y}$. □

Lemma 9. *Suppose the linear payoff environment with $G = U[0,\overline{y}]$. For any (small) $\varepsilon > 0$ there is $\beta\tau < 1$ large enough and $\overline{y}$ large enough, such that $\nu(\overline{y}) = \varepsilon$.*

Proof. Note that $\nu(y) = \frac{1}{1+\tau\beta_A\alpha(y)}$. Pick $L > \varepsilon^{-1} - 1$. By Lemma 8 for any $L > 0$, we can find $\beta\tau$ and $\breve{y}$ such that if $\overline{y} \geqslant \breve{y}$, $\tau\beta_A \geqslant L$. Since $\operatorname{supp} F = [0,1]$, we have from (7) that $\alpha(\overline{y}) = 1$ for $\overline{y}$ large enough. Therefore, $\nu(\overline{y}) = \frac{1}{1+\tau\beta_A\alpha(\overline{y})} < \frac{1}{1+L} < \varepsilon$. □

Lemma 10. *$\lambda \in \Delta(S)$ is x^*-upper-coarsening if and only if the corresponding Λ has the following form:*

$$\Lambda(z) = \begin{cases} \overline{\Lambda}(z), & z \in [0, x^*] \\ \overline{\Lambda}(x^*) + F(x^*)(z - x^*), & z \in (x^*, \mathbb{E}[x|x > x^*]) \\ \underline{\Lambda}(z), & z \in [\mathbb{E}[x|x > x^*], 1] \end{cases} \tag{17}$$

Proof of Lemma 3. Step 1. M and β_A are positively related. Indeed, when the mass of available sellers is X, the flow of matches is

$$M = \frac{1 - X}{\tau}.$$

The buyer arrival rate on available sellers is $\beta_A = \beta/X$. Therefore,

$$M = \frac{1 - \beta/\beta_A}{\tau}.$$

We are interested in the sign of $\delta M/\delta\Lambda$, therefore we will find $\delta\beta_A/\delta\Lambda$.

Step 2. The equilibrium values of $\alpha(y)$ and β_A are found from the system of equations

(7), which we reproduce here:

$$y - \hat{z}(y) = \tau\beta_A\Lambda(\hat{m}(y)), \quad \forall y \in Y; \tag{18}$$

$$\int \frac{dG(y)}{\tau\alpha(y) + 1/\beta_A} = \beta. \tag{19}$$

□

Proof of Lemma 4. Suppose the contrary, λ_0 is not upper-coarsening. I will show that there is a deviation from λ_0 that increases $\mathcal{J}$.

Let $\Lambda_0 \in \mathcal{L}$ which corresponds to λ_0. Let y^* be the zero of $\delta\mathcal{J}/\delta\Lambda$, and the corresponding cutoff in the seller optimization problem be $z^* = \hat{z}(y^*; \Lambda_0)$. I am now going to construct a feasible variation Λ^ε from Λ_0 that increases $\mathcal{J}$.

Let $\tilde{\Lambda}$ be the upper-coarsening (of the form (17)) that passes through point $(z^*, \Lambda_0(z^*))$. There is only one such function because there is only one line passing through $(z^*, \Lambda_0(z^*))$ and is tangential to $\overline{\Lambda}$. We have that $\Lambda_0(z) \geqslant \tilde{\Lambda}(z)$ on $z > z^*$, and $\Lambda_0(z) \leqslant \tilde{\Lambda}(z)$ on $z < z^*$. Moreover, since Λ_0 is not upper-coarsening, for some $z \in [0,1]$ one of these inequalities is strict. Consider variation

$$\Lambda^\varepsilon(z) = (\tilde{\Lambda}(z) - \Lambda_0(z))\varepsilon.$$

Since $\delta\mathcal{J}/\delta\Lambda < 0$ on $z > z^*$ and $\delta\mathcal{J}/\delta\Lambda > 0$ on $z < z^*$, Λ^ε increases $\mathcal{J}$. □

Proof of Proposition 4. Here I provide the entire complete proof. Step 1. By Lemma 3,

$$\begin{aligned} \frac{\delta\mathcal{J}}{\delta\Lambda} &= \gamma u \frac{\delta M}{\delta\Lambda} + (1-\gamma)\left(\frac{\delta M}{\delta\Lambda} K_2 + \nu(y)\beta_A\right) = \\ &= (\gamma u + K_2(1-\gamma))\frac{\delta M}{\delta\Lambda} + (1-\gamma)\beta_A\nu(y), \end{aligned} \tag{20}$$

where $K_2 > 0$. Evaluating with $G = U[0, \overline{y}]$,

$$\frac{\delta M}{\delta\Lambda} = K_1\overline{y}^{-1}(\nu(y) - \nu^2(y))' = K_1\overline{y}^{-1}(1 - 2\nu(y))\nu'(y), \tag{21}$$

where $K_1 > 0$. Since $\nu(0) = 1$ and $\nu(y)$ is non-negative and decreasing, $\delta\mathcal{J}/\delta\Lambda$ is either positive for all $y \in [0, \overline{y}]$ or crosses zero from above once. Let λ^*_γ denote the disclosure policy that maximizes $\mathcal{J}(\gamma)$. By Lemma 4, λ^*_γ is upper-coarsening.

Step 2. To see that the cutoff x^*_γ is decreasing in γ, note that larger γ puts more weight on the positive term in (20). Therefore the region of Y with negative $\delta\mathcal{J}/\delta\Lambda$ is smaller.

Step 3. Suppose $\beta\tau < 1/2$. Using Lemma 6, $\beta_A\tau \leqslant \beta\tau/(1-\beta\tau) < 1$. Next, $\nu(y) = (1+\beta_A\tau\alpha(y))^{-1} > (1+1\cdot 1)^{-1} = 1/2$ for any y. Using (21), $\frac{\delta M}{\delta\Lambda} \geqslant 0$ for any y, and so it $\delta\mathcal{J}/\delta\Lambda$. Therefore, full disclosure is optimal for any γ.

□

D Technical Extensions

D.1 No Excess Demand Assumption relaxed

Allow for the case when $\beta(1)\tau \geqslant 1$. If $\beta(1)\tau > 1$, then sellers get overwhelmed by the buyer requests and can't respond to all of them to the extent that they can't even reject them. To cover this situation we assume that if there are no available sellers to reject a pending buyer request, the platform rejects it automatically.

Since some requests can be rejected by the platform, the acceptance rate as perceived by buyers does not coincide with the acceptance rate α generated by sellers. Denote by α^e the effective acceptance rate that buyers face. Let at some moment of time there is $x \in [0, 1]$ mass of available sellers, and let buyers arrive to the platform at rate β. Then within the next time interval dt, there are βdt new request, and $x + \left(\frac{1-x}{\tau}dt\right)$ available sellers. What is α^e when sellers use acceptance rate α? Consider three cases.

1. $x > 0$. There is plenty of available sellers, $x + \left(\frac{1-x}{\tau}dt\right) > \beta dt$. Fraction α of buyers are accepted, therefore $\alpha^e = \alpha$.

2. $x = 0$ and $\alpha\beta < \frac{1}{\tau}$. There are few sellers that just became available but in sufficient

number to process all buyers. In the same fashion as in case 1, $\alpha^e = \alpha$.

3. $x = 0$ but $\alpha\beta \geqslant \frac{1}{\tau}$. Not sufficient sellers to process all buyers, some buyers are rejected by the platform. The number of accepted jobs is $\frac{1}{\tau}dt$. The acceptance rate is therefore $\alpha^e = \frac{1/\tau}{\beta}$.

Combining all there cases, we have that

$$\alpha^e = \min\{\alpha, \frac{1}{\tau\beta}\}.$$

The adjusted definition of equilibrium is then the following.

1.
$$\alpha \in [F(c^*(\beta_A)-), F(c^*(\beta_A)+)].$$

2.
$$\beta_A = \frac{\beta(\alpha^e)}{1-\beta(\alpha^e)\alpha^e\tau} = \begin{cases} \frac{\beta(\alpha)}{1-\beta(\alpha)\alpha\tau}, & \alpha\beta(\alpha)\tau < 1 \\ +\infty, & \alpha\beta(\alpha)\tau \geqslant 1 \end{cases}$$

$\beta_A = +\infty$ reflects the fact that when the demand is overwhelming, buyers line up for sellers so sellers start a new job immediately after they finish the previous one. The No Excess Demand assumption makes sure that this never happens, $\alpha\beta(\alpha)\tau < 1$ for all $\alpha \in [0, 1]$.

The next result shows that in the equilibrium there are no lines. By this reason for the clarity of exposition we decided to restrict the analysis to the case of no lines to begin with.

Claim. In equilibrium, $\beta_A < \infty$.

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