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

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PRELIMINARY AND INCOMPLETE

Abstract

I develop a model of a decentralized matching market in which buyers arrive over time and pursue sellers by proposing jobs. sellers have heterogeneous preferences over jobs and independently decide what jobs to accept. First, I establish that the equilibrium outcome is inefficient because of scheduling externality: by rejecting a job a seller makes himself available and decreases the other sellers' chances of getting subsequent jobs. Additionally, sellers fail to internalize buyers' search efforts. Second, I show that the platform's policy of coarse revelation of buyer information to sellers improves acceptance rates by decreasing the ability of sellers to "cherry-pick" desirable buyers. This degrades seller match quality but improves buyer welfare. Notably, this information coarsening can be Pareto improving because it offsets the scheduling externality. Finally, I characterize the disclosure policy that maximizes the number of matches in the linear payoff environment and show that, compared to the static case, there are additional availability and patience effects that qualitatively change the form of the optimal disclosure policy.

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1 Introduction

New platforms, such as Airbnb and Upwork, were created with the aspiration of bringing to the market the idle capacities possessed by dispersed owners. These platforms are matching marketplaces in the sense that both buyer and worker preferences are potentially highly heterogenous (Dinerstein *et al.* (2014); **?**); Cullen and Farronato (2015); **?**). Hence a platform's goal is to facilitate search and transactions between buyers and workers. In markets with pronounced heterogeneity, the information provision is the key because it improves matching efficiency (e.g. Hoppe *et al.* (2009)). Yet information availability also gives service providers more control over the matching process, grants them more market power that may lead to inferior market outcomes. This creates a tradeoff between matching efficiency and rent-seeking. The precise characterization and various consequences of this tradeoff constitute the theme of the present paper.

I develop a model of a *dynamic peer-to-peer market* in which buyers arrive stochastically and request services from workers; a participating worker has heterogenous matching value across buyers (e.g., heterogenous costs but posted price), his capacity is limited, and he is free to accept or reject buyer requests. Coarse segmentation of buyer tasks degrades matching quality for workers but also expands the set of equilibrium outcomes, namely it eliminates undesirable cream-skimming competition among workers. As a result, capacity utilization may increase. A combination of these two effects is that generically there exists a coarse segmentation of tasks on which the worker profits increase. Furthermore, buyers are also better off because higher capacity utilization implies shorter delays for buyers.

Dynamic peer-to-peer markets are increasingly relevant: there has been a 10-fold growth in worker participation in online platforms over the last 3 years (JP Morgan Chase, 2016). Nowadays 19% of the total US adult population has engaged in a sharing economy transaction (2015, PWC); Airbnb now lists more rooms than the three largest hotel chains combined (Fradkin); Uber has more drivers than taxi drivers in US. By 2025, online talent platforms could boost global GDP by $2.7 trillion (McKinsey, 2015).

Many existing platforms have the problem of failed matches. For example, **?** finds that hosts on Airbnb reject proposals to transact by searchers 49% of the time. Using TaskRabbit data (from June 2010 to May 2014), Cullen and Farronato (2015) find that only 49% of posted tasks were successfully completed. Horton (2015) provides empirical evidence from online labor market UpWork that information asymmetry about workers capacity impacts the formation of matches in important ways. Part of the failed matches occurs due to workers' picking out buyers[1]. In this paper I study how the platform can use segmentation of buyer tasks to improve the utilization rates, where utilization is defined as the fraction of the aggregate service providers' capacity being used on average.

Uber addressed the cream-skimming problem by limiting drivers rejection rate, and additionally hiding some passenger information from drivers, such as ride destination. Airbnb is also aware of the problem of worker low acceptance rate, and as a solution, introduced Instant Book feature. In my framework, a host who adopted Instant Book faces a single segment of guests so that he cannot discriminate among them. Airbnb is now working on fine tuning the Instant Book feature that would allow hosts to use a somewhat finer con-

[1] **?** reports that on Airbnb 20% of requests fail due to hosts' cream-skimming.

sumer segments. The natural question is how fine these segments should be allowed to be? TaskRabbit design defaults workers into accepting incoming tasks, so that rejecting tasks is harder because it requires additional actions. Moreover, TaskRabbit does not collect task details from customers before directing them to the search results. Offline markets which possess the same features as peer-to-peer platform are housing market, where the real-estate agency is the intermediary.

In a peer-to-peer market, coarsening the segmentation of consumer tasks can improve utilization rates. Workers can discriminate only across segments, and thus coarser segments limit the extent of discrimination. For intuition, consider a simple static example: there is one worker, his hourly rate p is posted in advance but the costs across potential tasks are heterogenous. The worker's optimal strategy is to accept all tasks with cost below p and reject the tasks with cost above p. The intermediary can increase the worker's acceptance rate by grouping tasks right above p with the tasks below p into one segment. The worker infers his expected cost for the segment. If the segment contains sufficiently many low-cost tasks, the average cost of a task from the segment is low enough, so that the worker is willing to accept a random task from the segment. Consequently, for any fixed price, the platform can increase the utilization rate by coarsening the segments of buyer tasks. This simple example, however, does not explain how segmentation influences the worker dynamic optimization problem and competition between workers, therefore we can't evaluate the equilibrium effect of segmentation and can't study implications for the welfare. Also in the example I assumed that the platform has complete information about the worker's cost, which would be a strong assumption in many applications.

Coarse segmentation may improve worker profits because information availability creates undesirable competition among workers for better buyers. Workers choose to keep their schedule open by ignoring low-return jobs in order to increase their individual chances of receiving high-return jobs. I call this behavior *dynamic cream-skimming.* Collectively, this behavior is sub-optimal for workers because all profitable jobs should be completed to maximize the joint profits. Dynamic cream-skimming results in wasted capacity and lowered worker profits.

Finally, I characterize the optimal segmentation for the intermediary that wants to maximize total matches, as a function of worker cost heterogeneity and the distribution of workers' productivity.

I proceed as follows. ...

1.1 Related Work

My paper is adjacent to several literatures.

First, vis-a-vis literature on pricing in two-sided platform (Rochet and Tirole (2006); Weyl (2010)), I make a point that in peer-to-peer markets, not only prices matter but also the matching mechanism. Second, vis-a-vis DAA literature which studies the centralized matching mechanism (kidney exchange, National Resident Matching Program), the markets I am interested in feature less control by the intermediary. The distinguishing feature of a peer-to-peer market is that a participant can typically decide whether to participate in a transaction or not after learning his counter-party. Intermediation in peer-to-peer platforms is therefore akin to regulation and anti-trust policies in industries. Third, peer-to-peer market is not a bargaining network often found in health (cite Robin Lee). The intermediary imposes some basic structure on the marketplace, such as posted prices.

Fourth, labor literature often assumes the black-box matching mechanism – matching function (Becker (1973); Shimer and Smith (2000)). This does not allow to evaluate the policies that affect the matching mechanism, such as information intermediation and minimal acceptance rate.

Fifth, on the search side of the platform, the interaction of product differentiation and search costs have been studied by Anderson and Renault (1999). They showed that when product differentiation increases, buyers search more. However, the total effect on price elasticity of demand is ambiguous. In the present paper the workers do not search but reject or accept incoming requests. Information coarsening decreases buyer task differentiation. On the one hand, workers are worse off because due to lack of information (Blackwell (1953)). On the other hand, information coarsening softens cream-skimming competition among workers.

There have been studies on dynamic matching markets and two-sided platforms in the literatures of economics and operations research. To the best of my knowledge, no prior work examined information disclosure in a dynamic mechanism design setting.

Our main contribution is to the market design literature. A related paper that also studies dynamic matching is Ashlagi *et al.* (2013). They show that waiting to thicken improves matching in kidney exchange because individual agents do not fully incorporate the benefits of waiting. I show there is a "reversed" effect: individual workers wait too long because they do not fully incorporate the lost value of rejection for buyers (or buyer waiting costs). Another related paper is Akbarpour *et al.* (2016).

Effects of information disclosure in matching markets are multi-dimensional. Hoppe *et al.* (2009) shows that disclosing too much information can induce excessive costly signaling which overcomes the gains from improved matching.

Milgrom (2010) shows that conflation increases prices of auctioned items if the items are identical and buyers have bidding costs. In his model, supply is fixed because the number of goods is pre-determined. Moreover, there is no cost of mismatch. In a closely related literature on targeting in advertising, Bergemann and Bonatti (2011) and Athey and Gans (2010) evaluate the economic implications of improved targeting on market for advertising. In both Bergemann and Bonatti (2011) and Athey and Gans (2010), better targeting increases demand for advertising (efficiency effect). Higher demand pushes prices up. In both papers, supply effect of better targeting gives the same effect on prices but the underlying mechanisms are distinct. In Bergemann and Bonatti (2011), better targeting leads to fewer advertisers in each outlet which lowers competition between advertisers and pushes prices down. In Athey and Gans (2010), better targeting allows each outlet to better allocate scarce advertising space, so that more advertisers can be accommodated. This pushes prices down.

Dinerstein *et al.* (2014) uses data from eBay to study ranking algorithms for differentiated products. In the framework of this paper, their Best Match algorithm is de-conflation of vertically differentiated goods. By making price a more important feature in search results, the goods are effectively grouped into price categories, so that it is now easier for buyers to find lower-priced goods.

Another closely related couple of papers is Hagiu and Wright (2015) and Hagiu and Wright (2016) that study the question of the intermediary's span of control in the platform it's running. There, the focus is on who, the platform or sellers, engages in complimentary activities (marketing, advertising). My explanation focuses on the matching mechanics and underscores the importance of buyer delays and supply heterogeneity in supply-demand fit.

My paper relies on communication games literature (Aumann *et al.* (1995); Grossman and Hart (1980); Milgrom (1981); Kamenica and Gentzkow (2011); Rayo and Segal (2012); Kolotilin *et al.* (2015); Bergemann *et al.* (2015)). Johnson and Myatt (2006) connect demand rotations to the company's information disclosure policy about its product. The contribution to this literature is that I study the effects of information coarsening on the market with network effects where one of the sides is potentially competitive. Bergemann and Morris (2013, 2016) examine the general question, in strategic many-player settings, of what behavior could arise in an incomplete information game if players observe additional information, private or public among themselves, that is not known to the analyst. Bergemann and Morris (2016) showed that a joint distribution over actions and states is Bayes correlated equilibrium if and only if it forms a Bayes Nash equilibrium distribution under some information structure. Bergemann and Morris (2013) illustrate how to find all BCE in linear best-response games with Gaussian uncertainty. Compared to them, the game the workers play in my model is asynchronous, there is no hidden common state but there are private types which are not observed by the intermediary.

There is extensive operations research literature on staffing and queuing problems for platforms. Gurvich *et al.* (2015); Banerjee *et al.* (2015) study price incentives schemes for staffing problem under uncertain demand but in both papers the supply side does not cream-skim. Cachon *et al.* (2015) shows that surge-price practices of ride-sharing platforms is nearly revenue-maximizing but also generates higher welfare than in the fixed-price or fixed-wage contract. Taylor (2016) and Arnosti *et al.* (2014) study how congestion affect the platform performance. Taylor (2016) show that congestion may have a counter-intuitive effect on optimal pricing in two-sided markets. Namely, in the presence of the uncertainty congestion may increase the optimal customer price and decrease the optimal wage. Arnosti *et al.* (2014) study the matching market when applicants can send multiple applications and employer's screening is costly. They show that if the screening cost is large enough, restricting the number of applications is strict Pareto improvement for both applicants and employers.

2 Model of Decentralized Matching Market

In this section I lay out a model of a decentralized matching market, in which buyers arrive gradually over time and pursue sellers by proposing a job; sellers have heterogenous preferences over buyers, seller capacities are limited, and sellers independently choose what matches to accept.

2.1 Setup

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

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 he decides whether to accept or reject them to maximize discounted profit flow. An accepted job takes time τ to complete, during which time the seller cannot receive new jobs. At each moment a seller is either available and waits for new jobs, or busy with working on a job.

There is a continuum of potential buyers who gradually arrive over time at flow rate β. That is, within a time interval dt, mass βdt of buyers arrive to the platform. Each buyer has a single job he wants to be completed. Upon arrival, the buyer proposes the job to one of the available sellers. I assume that the target seller is drawn uniformly at random from the pool of available workers. If the buyer's job is accepted, the buyer stays until the job is completed, otherwise he leaves the platform.

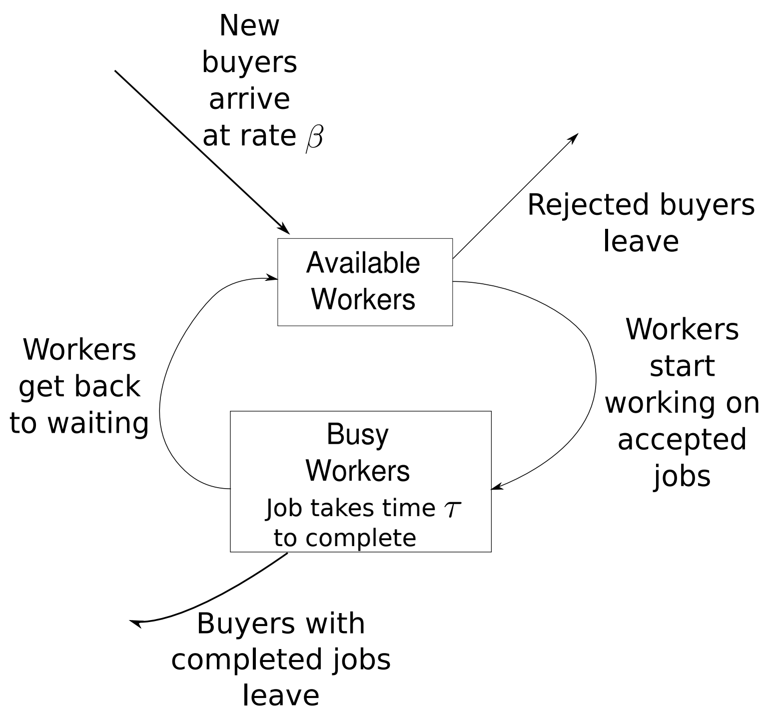
Assume $\beta\tau < 1$ which implies that collectively, it is physically possible for sellers to complete every buyer job. The assumption makes the exposition easier and relaxing it requires more notation to deal with either automatic rejections or queues. I do this in Appendix D and show that qualitatively results do not change.

The platform opts out of 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.

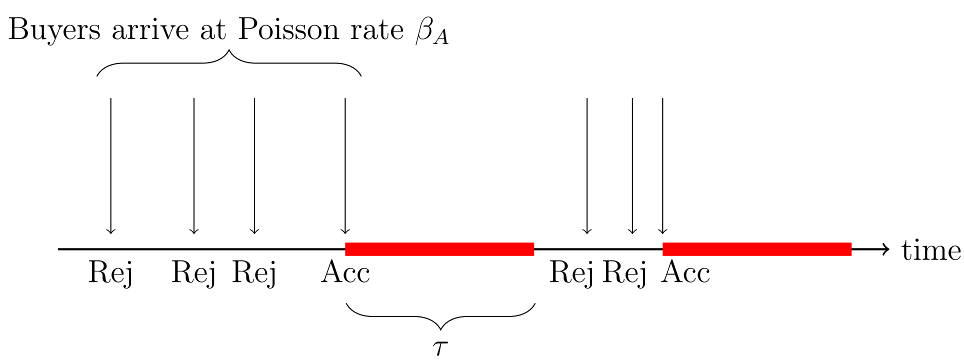
Heterogeneity and payoffs. There are two dimensions of heterogeneity in the matching market. First, each seller has heterogeneous match payoff across buyers. Second, different seller have different payoff functions over jobs. Concerning the platform's information disclosure problem, I need the following pieces of notation. Let x be buyer type, with the interpretation that x is the buyer characteristics observed by the platform.[2] The space of buyer types X is a compact subset of Euclidean space. Distribution of x is F with full support. Let y be seller type, with the interpretation that y is the seller characteristics unobserved by the platform.[3] The space of seller types Y is a compact subset of Euclidean

[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



(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 repeated search and waiting. An available seller receives requests at Poisson rate β_A. If a request is accepted, the seller becomes busy for time τ when he does not receive new requests.

Figure 1: Search and matching process.

space. 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:

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

Information Disclosure. The platform plays a signaling game with sellers. The platform observes buyer type x and chooses how to reveal it to sellers. Sellers do not receive any additional information about x outside of what the platform tells them. Let $S = \Delta(X)$ be the set of all posterior distributions over X. *Information disclosure policy* $\lambda \in \Delta(S)$ is a probability distribution of posteriors.[4] The interpretation is $s \in S$ 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 prior F.[6] The set of possible disclosure policies is then:

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

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 partially concealing some x's. 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.

Steady state. 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 of type-y available sellers, and let $\rho(y)$ be the type-y *utilization rate* – the fraction of type-y sellers who are busy. Denote the total fraction of busy sellers by $\bar{\rho} := \int_Y \rho(y)dG(y)$.

In a steady state, the flow of sellers who become busy is equal to the flow of workers who become available. The available-to-busy flow is equal to the buyer flow type-y sellers receive times their acceptance rate. Since buyer get distributed uniformly 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 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. Hence, in a steady

status, race, etc.

[4]When X is a compact subset of a Euclidean space, $\Delta(S)$ is the set of Borel-measurable 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.

[6]The two-stage lottery framework for disclosure is adopted from Bergemann *et al.* (2015).

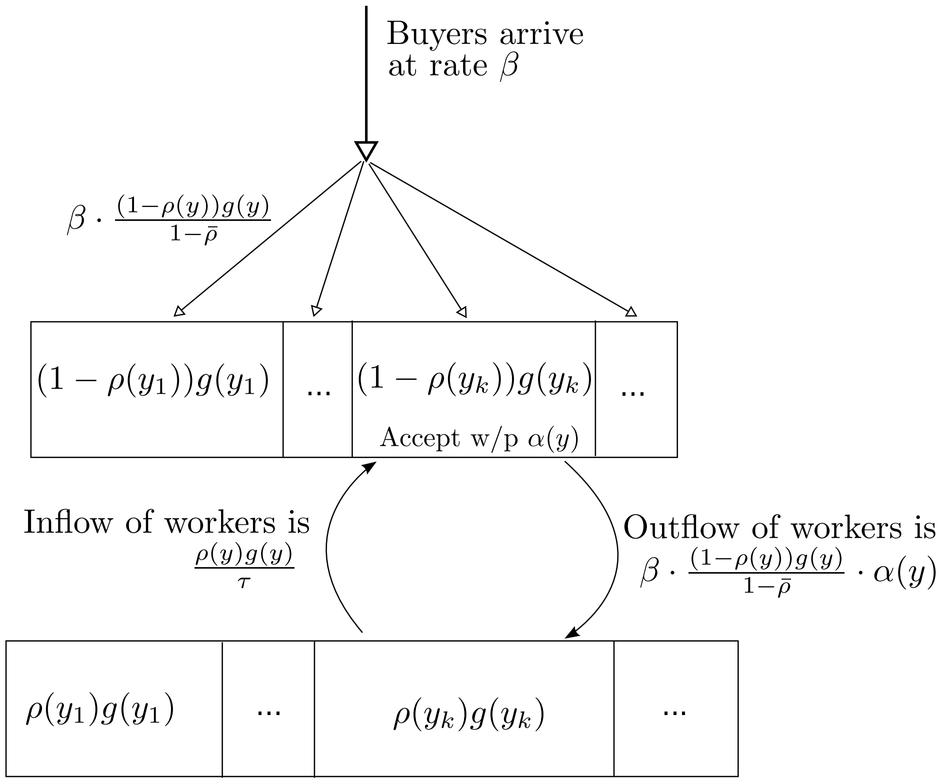


Figure 2: Matching process in a steady state. $g(y)$ is the mass of y-sellers, $\rho(y)$ is utilization rate, $\bar{\rho}$ is the average utilization rate.

state, we have:

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

See Figure 2 for the illustration.

Seller repeated search problem. Buyers arrive at flow rate β and get distributed uniformly at random across all available sellers. Therefore, each individual available seller experiences a Poisson arrival process of buyers, where the rate of the arrival is equal to the buyer-to-seller ratio:

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

(Myerson (2000)). There is thus a contrast between individual arrival process and aggregate arrival process in that the individual arrival process is stochastic while the aggregate arrival process is deterministic (a consequence of law of large numbers). More concretely, an individual seller faces a stochastic arrival process, such that over an infinitesimal time interval dt the probability that one buyer arrives is $\beta_A dt + o(dt)$. Jointly, available sellers face the deterministic buyer arrival process, such that over time interval dt the continuum mass $\beta_A dt$ of buyers arrive. As we show in the rest of this section, stochasticity of individual arrival process combined with independent decision-making creates seller coordination problem which results in matching inefficiency.

Each seller takes β_A as given[7] and solves the dynamic optimization problem where for each incoming job he observes the platform's signal s, and based on s, chooses to accept or reject the job in order to maximize his average profit flow. See Figure 1b for the illustration of the seller dynamic optimization problem. The expected profit for seller y of a job with signal s is $\pi(s, y) = \int_X \pi(x, y)s(dx)$. Denote by $V(y)$ the average profit flow when seller of type y acts optimally (value function)[8]. Denote by $v(s, y)$ the value of one new job with signal s, where v includes the option value of rejecting the job and the opportunity cost of being unavailable. 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. There is no discounting. Seller optimization problem is then the system of the following two equations:[9]

$$V(y) = \beta_A \int v(s, y)\lambda(ds) \tag{4}$$

$$v(s, y) = \max\{0, \pi(s, y) - \tau V(y)\} \tag{5}$$

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

$$\alpha(y) = \int \sigma(s, y)\lambda(ds). \tag{6}$$

2.2 Equilibrium

I am interested in a steady state equilibrium of the market in which the sellers take buyer arrival rate β_A as given and optimize independently, and the seller busy-available flows balance out. Recall that the exogenous objects in my model are: buyer flow rate β, profit function $\pi(x, y)$, distribution of types $G(y)$ and $F(x)$, and completion time τ. Based on the exogenous objects, a tuple $(\sigma, \bar\rho)$ constitute 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. [SS] Average utilization rate $\bar\rho$ arises in a steady state when sellers play σ, as shown in $\{$(2), (6)$\}$.

Proposition 1. *Steady-state equilibrium exists and is unique.*

In the proof in the Appendix, first, I show that for an arbitrary vector of acceptance rates $\alpha(y)$, there is a unique steady state. Then, average utilization $\bar\rho$ is increasing in $\alpha(y)$ for any $y \in Y$. The uniqueness of equilibrium obtains by monotonicity of reaction curves of α in $\bar\rho$

[7]This follows from the fact that there is a continuum of sellers on the platform, and so any individual seller's actions does not affect β_A.

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

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

and $\bar{\rho}$ in α. Namely, in (6), as buyer traffic intensity β_A increases, sellers become more picky and acceptance rate $\alpha(y)$ decreases. As $\alpha(y)$ increases, buyers get directed to a smaller set of sellers, hence β_A increases. For details see the proof in the Appendix on page 26.

2.3 Examples of Marketplaces

In this section I discuss how the model maps to the reality in the case of Uber, Airbnb and labor platform such as TaskRabbit. Recall that y denotes seller type, i.e. the seller's unobserved heterogeneity; x denotes buyer type, i.e. the information about buyer available to the platform.

Uber. Drivers receive requests from passenger when they are idle. y is driver's location, x is passenger's destination and star rating. Price per mile and minute is fixed (abstract away from surge pricing). Drivers do not like short rides or rides to the neighborhoods far removed from busy areas. Proposition 2 shows that if drivers have full discretion over accepting or rejecting, the driver utilization rates are inefficiently low, and the demand-supply fit is suboptimal.

Airbnb. Hosts are capacity constrained in rooms. Once a room is booked for a specific date, the host cannot accept a better guest. y - room quality, location. x - guest quality, e.g. college student vs. elderly couple. Every host sets his own price that applies to all guests but he may prefer to reject certain guests who he expects can be a pain in the neck. Proposition 2 shows that if hosts have full discretion over accepting or rejecting guest requests, the apartment utilization rates are inefficiently low, and the marketplace is removed from its full potential.

TaskRabbit. The service providers are capacity constrained because they can do only that many tasks per week. Once a service provider agreed to do some job, he is constrained in picking new tasks. y - seller skill, specialization. x - job category, job difficulty, professional/annoying client. Service provider sets hourly rate which applies to all tasks in the category. The seller may prefer to reject the tasks which he does not find to be a good fit, or too far, or bad timing of the lead. Proposition 2 shows that if service providers have full discretion over accepting or rejecting client leads, the utilization of participating labor is inefficiently low, and the matching efficiency is suboptimal.

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 help to avoid endogenous distributon of buyer types. It captures the 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 50%.

Assumption 2. *Buyers contact available sellers only.*

The goal of the paper is to explore the matching frictions that pertain to preference heterogeneity and screening. Therefore, I assume away the coordination frictions owing to several buyers requesting the same seller and the coordinatino frictions owing to buyer requesting unavailable sellers. All three types of matching frictions are present in the matching marketplaces[10]. 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 I assume away this channel of matching inefficiency to focus on screening.

Assumption 3 (Homogeneous Buyer Preferences)**.** *Buyers contact an available seller chosen uniformly at random*

This assumption has two implications. First, seller of any type faces the same intensity of buyer traffic. Second, each seller faces the same distribution of buyer jobs. This is a simplifying assumption that helps me to focus sellers excessive screening problem. In the extension subsection 4.1 I show how to deal with a more general demand system where demand for each seller type can be different.

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 easier and 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

This section studies the general platform's objective of maximizing the weighted average of buyer and seller surplus, which incorporates welfare maximization, profit maximization and maximizing the number of matches.

3.1 Seller coordination problem and crowding externality

This subsection establishes that the full disclosure market outcome is not Pareto optimal. In particular, it is not efficient. Reason — sellers' coordination problem. The inefficiency arises due to decentralization and dynamic nature of the matching.

To state the results of this and next sections, I need to define Pareto-optimality in my setting. Market outcome $O = (\{V(y)\}, CS)$ is a combination of seller profits and consumer surplus that arises in a steady-state equilibrium. 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

[10] Fradkin (2015)

O is Pareto-optimal if there is no other feasible O' such that $V(y)' > V(y)$ for all y, and $CS' > CS$. The Pareto frontier is the set of all Pareto-optimal outcomes. We say that 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 seller profits. A market outcome is *efficient* if there is no other feasible outcome with higher welfare.

Write $V^\sigma(y)$, $\rho^\sigma(y)$, CS^σ for steady-state profits, utilization rates and consumer surplus when strategy profile σ is played. Imagaine the platform starts with the full disclosure as its default disclosure policy. The next proposition shows that there is a feasible outcome at which sellers are strictly better off than under the full disclosure, they complete more jobs, and additionally, the buyers are also better off. The result implies that there is a coordination problem among sellers.

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

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

The full proof is in the Appendix. Here I give the sketch of the proof for the case of identical sellers, which gives 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. Therefore, the opportunity cost of accepting τV^{FD} is strictly positive, too (see Eq. (5)). As a result, in equilibrium, the accepted jobs are those with profits $\pi \geqslant \tau V^{FD}$. However, the profitable jobs are those with $\pi \geqslant 0$. Hence, some profitable jobs are rejected. Consider strategy $\tilde{\sigma}$ that maximizes the joint seller profits. It prescribes every seller to accept jobs with $\pi \geqslant 0$ (and this is feasible by the No Excess Demand assumption). Naturally, $\tilde{\sigma}$ yields $\tilde{V} > V^{FD}$. It also increases acceptance rate, and thus the utilization rates, $\tilde{\rho} > \rho^{FD}$. Consumers are better off because consumer surplus is increasing in the acceptance rate.

A very high-level intuition for the coordination problem is the folllwing. 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.

Interestingly, that unlike in the price competition, that benefits buyers and improves market efficiency, seller coordination problem in this setting results in inefficient outcome with both lower buyer and seller surplus. This is a market failure. I attribute the source of the failure to the *crowding externality* generated by sellers. 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 crowding externality to arise is the dynamic nature of matching and dispersed seller capacities.

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 workers 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.

Now we know that the full disclosure outcome is Pareto dominated by some strategy profile $\tilde{\sigma}$. A natural question is whether there is 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.

3.2 Optimal information disclosure with identical sellers

I start by considering the case of identical sellers, i.e. singleton Y. 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, CS) *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, with only one type of acceptable jobs, there is no option value of rejecting a profitable jobs. All profitable jobs are the same! Since a Pareto optimal outcome is feasible with $V \geqslant 0$, sellers have incentives to follow the platform's recommendations. 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 $\gamma V + (1-\gamma)CS$ for some $\gamma \in [0, 1]$. Figure 3 illustrates the result. From Proposition 2 we know that the full disclosure outcome is suboptimal. The welfare maximization policy corresponds to $\gamma = 1/2$.

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) while my model is a signaling game with dynamically optimizing receivers. This dynamism is the novel element not present in the prior literature on information disclosure.

Disclosure of buyer characteristics to sellers has three competing effects on welfare. The first 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,

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

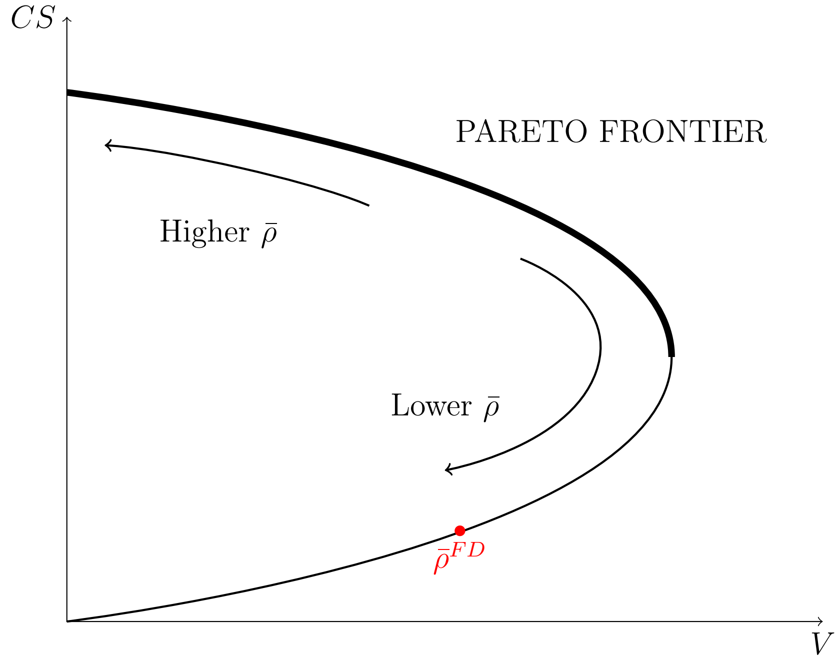


Figure 3: Utility possibility set for buyer surplus and seller profits. Disclosure policy can implement any point on the Pareto frontier (thick solid line). The full disclosure outcome, marked with $\bar{\rho}^{FD}$, is subtoptimal.

jobs. It results in higher rejection rates that "slows down" the buyer side of the market. 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 coarsening λ' such that $CS' > CS''$.

The third effect is the *Seller Option Value effect*. More information available to sellers increases their ability to "cherry-pick" the best jobs, and so creates the positive option value of rejecting. In equilibrium, it hurts seller surplus because it is not efficient 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 $\tau V' \leqslant \tau V''$.

Both Delaying and Option Value effects lead to sellers' *excessive screening* — rejection rates are inefficiently high. The Individual choice effect gives a motive to the platform to release information while the Delaying and the Option Value effects give a motive to conceal information. The Delaying and the Option Value effects are the consequences 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)).

When workers are identical, achieving efficiency requires coarse information disclosure policy because the Delaying effect and the Option Value effects win over the Individual Choice effect. Denote the efficient disclosure policy by $\hat{\lambda}$ and the set of efficients matches by $\hat{X}_a := \{x \in X : \pi(x) + u(x) \geqslant 0\}$. 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 full disclosure, the accepted jobs are $X_a^{FD} := \{x \in X : \pi(x) \geqslant \tau V^{FD}\}$. Note that X_A^{FD} is a proper subset of $\hat{X}_a$. There are two souces of inefficiency under full disclosure. 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 Delaying effect. Jobs $\{x \colon 0 \leqslant \pi(x) \leqslant \tau V\}$ are rejected because sellers fail to internalize the crowding externality they impose on each other. This is the Option Value effect.

How does the efficient disclosure policy $\hat{\lambda}$ depends on the economic primitives of the market? What is interesting is that $\hat{\lambda}$ does not depend on the intensity of buyer traffic β (optimal disclosure for other γ have this property, too). This implies that $\hat{\lambda}$ is the same disclosure policy as would be optimal in a static case, when $\tau = 0$.

Proposition 4. *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 search costs are higher, $\hat{\lambda}$ prescribes pooling more of marginal unprofitable jobs with inframarginal profitable jobs.*

Independence of $\hat{\lambda}$ from β and τ happens because the arrival rate to available sellers β_A matters only to the extent that it creates option value of rejection. When the sellers are identical, the efficient $\hat{\lambda}$ induces the posterior mean distribution $F^{\hat{\lambda}}$ of payoffs that has only one acceptable value. Therefore, the option value is zero, and so β does not matter.

3.3 Optimal information disclosure with heterogeneous sellers

Typically, the platform observes seller preferences imperfectly, and there is seller preference component that is known only to the seller (skill level, willingness to do long rides, etc). If there is privately known match value held by sellers, the intermediary's ability to influence the market outcome using information design is limited. Depending on the distribution of seller types, there may or may not exist a coarse disclosure policy that improves acceptance rates. In this section I provide sufficient conditions for this.

To see the intuition behind additional problems the platform faces when sellers have private information, imagine two types of sellers: professionals and amateurs. Professionals can profitably complete a larger set of jobs than amateurs. When the platform designs the disclosure policy, it should take into consideration different effects the disclosure policy will have on the two groups of sellers. Amateurs can only do a small subset of jobs, and so they require more information to be able to profitable complete any jobs. If insufficient information is provided, they reject all jobs because they cannot tell apart profitable jobs from the unprofitable jobs. On the other hand, more disclosure makes the professionals more picky and decreases their acceptance rate. The resolution of this tradeoff depends on the relative sizes of amateur and professional populations. If there are more professionals than amateurs, then less disclosure increases the total acceptance rates even though amateurs stop working. If there are more amateurs, coarse disclosure policy decreases the total acceptance rate. In the rest of this section we study this problem for the general continuous distribution of seller types.

Let the space of buyer types be $X = [0, 1]$, with the interpretation x is the difficulty of the job. Let the space of seller types be $Y = [0, \overline{y}]$, $\overline{y} \geqslant 1$, with the interpretation that y is the seller skill level. The seller profit function is $\pi(x, y) = y - x$. "Professionals" are the sellers with high y, and "amateurs" are the sellers with low y. Buyer match value is $u(x, y) = u$. I call this *linear payoff* environment.

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

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

where $V = \int_Y V(y)dG(y)$, and $CS = u \cdot M$, where M is the total number of matches formed over unit of time.

The goal of this subsection is to demonstrate that the dynamism of seller optimization problme creates qualitatively new effects compared to the static matching. This goal motivates the choice of the linear payoff environment. From the prior literature it is known that when the distribution of seller types is uniform, the disclosure policy has no effect on the total number of matches. For the non-uniform distributions, the optimal disclosure policy depends on whether the probability density funciton is decreasing or increasing.

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

- *If g is decreasing, then full disclosure is optimal;*
- *If g is increasing, 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 next result shows that the optimal disclosure policy in the case of the uniform distribution of seller types depends on the intensity of buyer traffic β and tightness of seller capacity constraints τ.

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

Proposition 5. *Suppose $G = U[0, \overline{y}]$, $\overline{y} \geqslant 1$. Then there is unique $x^* \in X$ such that x^*-lower-censorship is optimal.*
Furthermore,

- *if $0 < \beta\tau < 1/2$, then $x^* = 1$ (no disclosure is strictly optimal)*
- *if $\bar{y}$ is large enough, then there is $\chi^* \in (1/2, 1)$ such that if $\beta\tau > \chi^*$, then $x^* < 1$ (some coarsening is strictly optimal)*

To better understand the mechanics behind the result and the role of the dynamic screening, consider two simplifications of the model. In the first one, sellers optimize dynamically but are perfectly replenished, so that the pool of available sellers is always 1. In the second simplification, sellers availability is endogenous but they are myopic, i.e. have zero option value of rejection.

Corollary 1. *Suppose $G = U[0,1]$. If sellers are perfectly replenished, then no disclsure is strictly optimal to maximize the matching rate.*

The results explains the interplay between the Seller Individual Choice effect, Buyer-side effect and the Seller Option Value effect. In one-shot matching, concealing information decreases the acceptance rat of low-type sellers but increases the acceptance rate of high-type sellers. With uniform distribution of seller types, this two effects cancel out and the total matching rate is unchanged (Fact 1). When sellers optimize dynamically, less information also decreases their option value of rejection and further increases the acceptance rate. Therefore, the statement of 1.

Corollary 2. *Suppose $G = U[0,1]$. If sellers are myopic, then full disclsure is strictly optimal to maximize the matching rate.*

In this result, we shut down the Option Value effect of information disclosure and focus on the effect of endogenous distribution of seller types. Indeed, in the equilibrium, the pdf of available seller types is $\nu(y)/\bar{\nu}$. Since $\nu(y)$ is decreasing, the effective pdf of seller types is decreasing. By the result from the static matching (Fact 1) we know that full disclosure maximizes matching rate. 2 confirms that this is indeed the case.

3.4 Main Lemma and the Proof

Denote the posterior mean of x conditional on signal s by $z(s) := \int_X xs(dx)$. I reservae notation z for a typical posterior mean of x. Denote by F^λ the distribution of posterior means of x when the platform uses disclosure policy λ. Define the *option value function* $\Lambda\colon [0,1] \to \mathbb{R}_+$:

$$\Lambda(z;\lambda) := \int_0^z (z-y)dF^\lambda(y), \tag{7}$$

For any λ, $\Lambda(z)$ is non-negative, weakly increasing from 0 to $1 - \mathbb{E}[x]$, and is convex. As we will see from the next lemma, $\Lambda(z)$ is equal to the option value of rejecting a job with expected difficulty z.

The next lemma shows that a seller's optimization problem depends on λ only through Λ^λ.

Lemma 1. *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:*

$$V(y) = \frac{y - \hat{z}(y)}{\tau} = \beta_A \Lambda(\hat{z}(y)). \tag{8}$$

Let $\overline{\Lambda}$ be the option value function under full disclosure, $\overline{\Lambda}(z) := \int_0^z (z-x)dF(x)$. Similarly, let $\underline{\Lambda}$ be the option value function under no information, $\underline{\Lambda}(z) := \max\{0, z - \mathbb{E}[x]\}$. Denote by $\mathcal{S}$ the set of all option value functions Λ implementable by some λ. The next lemma characterizes $*$.

Lemma 2. *Option value function Λ is implementable by some disclosure policy if and only if Λ is a convex function point-wise between $\overline{\Lambda}$ and $\underline{\Lambda}$.*

The result is shown in e.g. Gentzkow and Kamenica (2016). The power of Lemma 2 is that it shows that any disclosure policy can be represented as some non-negative, non-decreasing and convex function Λ. Therefore, in any optimization problem that requires to find an optimal signaling structure, it is equivalent to find an optimal $\Lambda \in \mathcal{S}$. It is easier to optimize with respect to $\Lambda \in \mathcal{S}$ because the platform's optimization problem is more tractable when the set of optimizers is bounded convex functions.

Denote the flow of matches consummated on the platform by M, i.e. over time period dt, mass $M dt$ of matches is consummated. Consider the platform's problem of maximizing the utilization rate. Since we hold seller participation fixed, the problem is equivalent to maximizing M. In light of Lemma 2, the platform's problem can be expressed as

$$\max_{\Lambda \in \mathcal{S}} M.$$

The problem is not trivial because: 1) sellers are heterogenous; 2) besides the direct effect of disclosure policy on seller's dynamic optimization problem in (8), there is an equilibrium effect when arrival rate β_A changes in response to the sellers' change in acceptance rate, as shown in Eq. (**??**). We approach this problem using calculus of variations. Denote by $\nu(y) := x(y)/g(y)$ the fraction of available type-y sellers relative to all type-y sellers.

Lemma 3 (Main Lemma)**.** *The first variation of M with respect to Λ exists and is proportional to:*

$$\frac{\delta M}{\delta \Lambda} \propto -(g(y)\nu^2(y))' + g(y)\nu'(y). \tag{9}$$

A way to see the contribution of lemma Lemma 3 is to compare it with the static case which has been studied in the prior literature. The seller's problem becomes static when $\tau = 0$. A variation of the following result has been shown in Kolotilin *et al.* (2015), and the implied concavification reasoning goes back to Aumann *et al.* (1995) and Kamenica and Gentzkow (2011).

Corollary 3. *Suppose $\tau = 0$. Then*

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

If G is concave, then full disclosure is optimal. If G is convex, no disclosure is optimal.

The result easily follows from lemma Lemma 3 after noting that $\nu(y) = (1 + \tau\beta_A\alpha(y))^{-1}$.

When matching is dynamic, the original formula (10) has to be adjusted for the dynamic effects, as shown in (9). I now explain the additional dynamic effects in more detail.

To better understand the additional effects, consider uniform distribution of seller types, $G = U[0, 1]$. Under uniform distribution in the static case, the disclosure policy does not matter: $\frac{\delta M}{\delta \Lambda} = 0$ for any Λ. In my model, however, we have that

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

There are two additional forces that the intermediary has to consider when the matching problem becomes dynamic: *availability effect* and *patience effect*. The availability effect arises because in equilibrium, high types are less available than low types. This makes the effective distribution of sellers concave, and creates a motive for the intermediary to use finer disclosure policy. Term $\nu^2(y)$ in the expression above is responsible for the availability effect.

The patience effect arises because sellers do not act myopically and may reject jobs due to temporal optimization. High types have greater option value of rejecting a job, and so all held equal they are more picky than low types. Note that this effect is dynamic and is distinct from the pure static effect of high types having higher match value. Relatively higher pickiness of high types creates a motive for the intermediary to coarsen disclosure for high types. Term $-\nu(y)$ in the expression above is responsible for the patience effect.

4 Extensions

4.1 General demand: sellers are imperfect substitutes

seller type space Y is finite. There is a continuum of potential buyers who arrive continuously over time. Let $\beta(y)$ be the flow rate of buyers who arrive to request services of type-y sellers. In other words, within an infinitesimal time interval dt, a continuum mass $\beta(y)dt$ of buyers arrive to the platform and requests one of type-y sellers. I refer to the collection of functions $\{\beta(y)\}_{y\in Y}$ as "demand" although it is different from the textbook notion of demand in that my demand arrives continuously. We make the following assumptions on the demand.

Assumption 5 (Frictional Consumer Search)**.** *Let the fraction of available type-y sellers relative to the mass of all available sellers be* $\nu(y)= x(y)/\sum x(y')$. *Demand for type-y sellers is*

$$\beta(y) = \beta(y, \alpha(y), p_y, \nu(y)).$$

β *is differentiable in* α, p *and* ν. *Most importantly,*

$$\frac{\partial \beta}{\partial \nu} \geqslant 0. \tag{11}$$

The assumption posits that the demand for type-y sellers depends not only on the characteristics of type-y sellers but also on their number. Critically, the larger the fraction of available type-y sellers, the more demand they receive.

The steady state condition becomes:

$$\beta(y)\alpha(y) = \frac{g(y) - x(y)}{\tau}, \quad \forall y \in Y. \tag{12}$$

Each buyer type now had individual buyer arrival rate:

$$\beta_A(y) := \frac{\beta(y)}{x(y)} \tag{13}$$

A tuple of endogenous objects $(\alpha(y), x(y), \beta_A(y))_{y\in Y}$ constitute a *steady-state equilibrium* if

1. sellers act optimally taking buyer arrival rate $\beta_A(y)$ as given, so that the acceptance rates $\alpha(y)$ are determined by (6).

2. Given $\alpha(\cdot)$, seller flows balance out, as shown in (12). Steady state flows determine $\beta_A(y)$ according to (13).

Assumption 6 (No Excess Demand-2)**.** *Collectively, it is physically possible for sellers to complete every buyer job:* $\beta(y, 1, p(y), 1)\tau < g(y)$ *for all* $y \in Y$.

Proposition 6. *Steady-state equilibrium exists and is unique.*

First I establish that for any vector of acceptance rates $\alpha(y)$, there exists a unique steady state masses of available sellers $x(y)$, as a solution to (12) (lemma Lemma 4). The existence of $\{x(y)\}$ crucially relies on the No Excess Demand assumption, and the uniquess follows from the fact that demand depends on $\{x(y)\}$ through the share $\nu(y)= x(y)/\sum x(y')$. Then treating x as a funciton of α, I show that there is a unique solution $(\alpha(y), \beta_A(y))_{y\in Y}$ to $\{$(6), (13)$\}$. For details see the proof in the Appendix on page 29.

Proposition 7. *Let* σ^{FD} *be the equilibrium strategy profile under full disclosure. Then there exists* $\tilde{\sigma}$ *such that for all* y*:*

$$\begin{aligned} \tilde{V}(y) &> V^{FD}(y), \\ \tilde{\rho}(y) &> \rho^{FD}(y), \\ \widetilde{CS} &\geqslant CS^{FD}. \end{aligned}$$

4.2 Endogenous price

In our base model we assumed that the price is set by the larger outside market. In this section we consider other scenarios of price setting: competitive price and price set by the intermediary. Main results of this section are: 1) there is a continuum of competitive price equilibria; 2) characterization of #matches-maximizing pricing.

We adjust our notation a little bit to account for the fact that demand depends on price. Namely, buyer arrival rate is given by

$$\beta(\alpha, p),$$

$\beta(0, p) = 0$, $\beta_\alpha > 0$, $\beta_p < 0$. The assumption I am making here is that buyer arrival rate responds to the changes in platform policies only through the average acceptance rate α and price p.[11] Denote demand elasticities wrt α and wrt p by $\varepsilon_\alpha = \frac{\beta_\alpha \alpha}{\beta} > 0$ and $\varepsilon_p = -\frac{\beta_p p}{\beta} > 0$, respectively.

[11] Let buyer i's expected acceptance rate for his job be α_i, the expected match value conditional on being matched be v_i. Additionally, buyer i has hassle cost f_i from using the platform. If the buyer does not use the platform he gets payoff of zero. If he uses the platform he experiences a disutility of f_i. After requesting a service, if he is accepted, he pays price p and gets payoff of v_i. Therefore, buyer i joins iff

$$\alpha_i(v_i - p) - f_i \geqslant 0.$$

As defined above, the average acceptance rate across buyers is α. The assumption is that [#potential buyers]$\cdot$ $\Pr(\alpha_i(v_i - p) - f_i \geqslant 0) = \beta(\alpha, p)$.

4.3 Price set by the intermediary

In this section we study a situation when the platform controls the price on the platform (e.g. in case of Uber and Instacart). This brings us closer to the literature on pricing in two-sided markets (Rochet and Tirole (2006); Weyl (2010)). However, unlike these papers, we are more specific about where the network effect is coming from and also sellers have a decision margin not related to participation – acceptance rate.

Match-maximizing platform. From the previous section we know that whatever price a Walrasian auctioneer picks, it can be sustained in a competitive equilibrium. We thus pose a question: if the platform can set the price, what price and disclosure policy should it use to maximize the number of matches? The platform solves

$$\max_{\lambda,p} \alpha\beta(\alpha,p),$$

subject to {(4), (5)}.

We know from Proposition 3 the form of the optimal disclosure policy for given price. How should the price be set? To induce more demand, the platform would like to choose lower price. But the lower the price, the lower seller utilization rate can be implemented. The next result quantifies this tradeoff.

Proposition 8. *Assume sellers have no private information. The #matches-maximizing disclosure policy has the form*

$$\hat{\lambda}(x) = \begin{cases} \mathbb{E}[x|x \leqslant mc], & \alpha \\ \mathbb{E}[x|x > mc], & 1-\alpha \end{cases}$$

and α, p and mc solve the system of equations

$$\begin{aligned} \mathbb{E}[x|x \leqslant mc] &= p \\ F(mc) &= \alpha \\ \frac{\varepsilon_\alpha + 1}{\varepsilon_p} &= \frac{mc - p}{p} \end{aligned} \tag{14}$$

The proof is the Appendix on page ??. From (14) note that $mc > p$, which is indication of the platform taking into account network effects, namely the demand expansion for higher α.

Revenue-maximizing platform. When the platform in the stage of growth, it wants to be bigger. Later on, the platform turn to monetization. We are interested in answering the following question: How does the platform policies change when it is profit-maximizing?

To get a cut from sellers revenue, the platform uses two prices: price p for buyers and wage w for sellers. Additionally, it has disclosure policy as an instrument. The platform's objective is

$$\begin{aligned} &\max_{\lambda,p,w} \beta(\alpha,p)\alpha(p-w) \\ \text{s.t.}\quad & AC(\alpha) \leqslant w \end{aligned}$$

and subject to {(4), (5)}.

Proposition 9. *Assume sellers have no private information. The profit-maximizing disclosure policy has the form*

$$\hat{\lambda}(x) = \begin{cases} \mathbb{E}[x|x \leqslant mc], & \alpha \\ \mathbb{E}[x|x > mc], & 1-\alpha \end{cases}$$

and α, p, w and mc solve the system of equations

$$\begin{aligned} \mathbb{E}[x|x \leqslant mc] &= w \\ F(mc) &= \alpha \\ \frac{1}{\varepsilon_p} &= \frac{p-w}{p} \\ \frac{\varepsilon_\alpha + 1}{\varepsilon_p} &= \frac{mc-w}{p} \end{aligned}$$

The next results states how the marketplace variables change after the platform transitions from the match-maximizing mode to the revenue-maximizing mode. Imagine the platform starts with match-maximizing as in Proposition 8. It makes zero revenue there because it takes zero fee on transactions. There are two ways to increase the intermediary's revenue. One is increase buy price, the other one is to decrease the wage. However, decreasing w decreases acceptance rate α, so it might be profitable to increase both p and w. Depending on the properties of the demand, the platform may find it optimal either to increase both p and w, or decrease both p and w, or increase p and decrease w. The next result provides sufficient conditions for when the acceptance rate is higher (lower) under profit-maximization than under match-maximization.

Conjecture 1. *If $\beta_p + \alpha\beta_{\alpha p} > 0$, $\beta_{pp} > 0$, then $\alpha^{PM} < \alpha^{MM}$ and $w^{PM} < p^{MM}$. If $\beta_{pp} < 0$, $\beta_{\alpha p} < 0$, then $\alpha^{PM} > \alpha^{MM}$ and $w^{PM} > p^{MM}$.*

5 Conclusion

6 Appendix

A Lemmas

Lemma 4. *For any vector $\alpha(y)$, there exists a unique vector solution $x(y)$ to (2).*

Proof. Denote $x = \sum_{y'} x(y')$ the mass of all available sellers. Rewrite (2) as

$$\tau\beta(y, \alpha(y), p_y, x(y)/x)\alpha(y) + x(y) = g(y). \tag{15}$$

Denote the left-hand side of the equation by $\mathbf{A}(\mathbf{x})$, where $\mathbf{x} = (x(y))_{y \in Y}$ and $\mathbf{A}$ is a correspondence that maps $\mathbf{x}$ into $\mathbb{R}^{dimY}$. First we show that the solution to $\mathbf{A}(\mathbf{x}) = \mathbf{g}$ exists, then we show that it is unique.

For existence, consider a mapping T defined as

$$T_i(\mathbf{x}) = g_i - \tau\beta(y_i, \alpha(y_i), p_{y_i}, x(y_i)/x)\alpha(y_i).$$

Define $X = \{(x_1, ... x_{\dim Y})\colon 0 \leqslant x_i \leqslant g_i\}$. We will show that mapping T satisfies the conditions of Brouwer's fixed point theorem. First, T maps X to itself. Indeed, $T_i(\mathbf{x}) \leqslant g_i$. But also

$$T_i(\mathbf{x}) \geqslant g_i - \tau\beta(y_i, 1, p_{y_i}, 1) > 0.$$

The first inequality uses Assumption 5 and demand monotonicity in α. The second inequality uses **??**. Second, X is compact. Finally, T is continuous. Therefore, Brouwer's theorem ensures the existence of a fixed point, which is a solution to (15).

In the rest of the proof we prove uniqueness. We will show that the principal minors of Jacobian matrix of $\mathbf{A}$ are non-negative everywhere. Then by Gale-Nikaido (1965), the mapping is one-to-one and hence $\mathbf{A}(\mathbf{x}) = \mathbf{g}$ has a unique solution.

$$J = \begin{bmatrix} \frac{\partial A_1}{\partial x_1} & \frac{\partial A_1}{\partial x_2} & \cdots \\ \frac{\partial A_2}{\partial x_1} & \frac{\partial A_2}{\partial x_2} & \\ \vdots & & \ddots \end{bmatrix},$$

where we use a simplified notation $x_1 := x(y_1)$. Use notation $\nu_1 = x_1/x$.

$$\begin{aligned} \frac{\partial A_1}{\partial x_1} &= \tau \frac{d\beta(y_1, \alpha(y_1), p_{y_1}, x(y_1)/x)\alpha(y_1)}{d\nu_1} \frac{d(x(y_1)/x)}{dx_1} + 1 = \\ &= \tau \frac{d\beta(y_1, \alpha(y_1), p_{y_1}, x(y_1)/x)\alpha(y_1)}{d\nu_1} \frac{x - x_1}{x^2} + 1. \end{aligned}$$

Denote for brevity $\beta_1 = \frac{d\beta(y_1, \alpha(y_1), p_{y_1}, x(y_1)/x)\alpha(y_1)}{d\nu_1}$. Then

$$\frac{\partial A_1}{\partial x_1} = \frac{\tau}{x}\beta_1(1 - \nu_1) + 1.$$

Similary find

$$\frac{\partial A_1}{\partial x_2} = -\frac{\tau}{x}\beta_1\nu_1.$$

We need to show that all principle minors of matrix J are non-negative. Without loss of generality, consider the leading principal minor of size $K = 1, ..., \dim Y$, denote it by J_K. It can be rewritten as follows

$$J_K = \begin{bmatrix} 1 + \frac{\tau}{x}\beta_1 & \cdots & 0 \\ \vdots & \ddots & \\ 0 & & 1 + \frac{\tau}{x}\beta_K \end{bmatrix} + \frac{\tau}{x} \begin{bmatrix} -\beta_1\nu_1 \\ \vdots \\ -\beta_2\nu_2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}.$$

Now I will use the following formula for the determinants:

$$\det(X + AB) = \det X \det(I + BX^{-1}A).$$

In case of matrix J_K, we obtain:

$$\det J_K = \det \begin{bmatrix} 1 + \frac{\tau}{x}\beta_1 & \cdots & 0 \\ \vdots & \ddots & \\ 0 & & 1 + \frac{\tau}{x}\beta_K \end{bmatrix} \det(1 + \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 + \frac{\tau}{x}\beta_1 & \cdots & 0 \\ \vdots & \ddots & \\ 0 & & 1 + \frac{\tau}{x}\beta_K \end{bmatrix}^{-1} \frac{\tau}{x} \begin{bmatrix} -\beta_1\nu_1 \\ \vdots \\ -\beta_2\nu_2 \end{bmatrix}).$$

We need to show that $\det J_K \geqslant 0$ for all $\mathbf{x}$. It is sufficient to the second determinant on the right hand side of the formula above. We need to show

$$1 + \frac{\tau}{x}\sum_{i=1}^{K}\frac{-\beta_i\nu_i}{1+\frac{\tau}{x}\beta_i} \geqslant 0.$$

First observe that $\frac{\beta_i\tau/x}{\beta_i\tau/x+1} \leqslant 1$, and then

$$1 + \frac{\tau}{x}\sum_{i=1}^{K}\frac{-\beta_i\nu_i}{1+\frac{\tau}{x}\beta_i} \geqslant 1 - \sum_{i=1}^{K}\nu_i \geqslant 0,$$

because $\sum_{i=1}^{\dim Y}\nu_i = 1$. This proves that all principal minors of J are non-negative, and by Gale-Nikaido (1965), $\mathbf{A}(\mathbf{x}) = \mathbf{g}$ has a unique solutions. ☐

B Proofs omitted from the main text

Proof of Proposition 1. We need to show that there is a unique solution $(\alpha(y), \beta_A(y))_{y\in Y}$ to $\{(6), (\textbf{??})\}$

Use Kakutani theorem. ☐

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 (5) 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

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

☐

Proof of lemma 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 (8) and (**??**), which we reproduce here:

$$y - \hat{z}(y) = \tau\beta_A\Lambda(\hat{m}(y)), \quad \forall y \in Y; \tag{16}$$

$$\int \frac{dG(y)}{\tau\alpha(y) + 1/\beta_A} = \beta. \tag{17}$$

Take the differential of (17):

$$-\int \frac{dG(y)\left(\tau\delta\alpha(y) - \delta\beta_A/\beta_A^2\right)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} = 0.$$

$$\frac{\delta\beta_A}{\beta_A^2}\int \frac{dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} - \tau\int \frac{\delta\alpha(y)dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} = 0.$$

$$\delta\beta_A = \frac{\tau\int \frac{\delta\alpha(y)dG(y)}{\left(\tau\alpha(y)+1/\beta_A\right)^2}}{\frac{1}{\beta_A^2}\int \frac{dG(y)}{\left(\tau\alpha(y)+1/\beta_A\right)^2}}. \tag{18}$$

Now use the fact that

$$\alpha(y) = \Lambda'(\hat{m}(y)+) \tag{19}$$

to find the differential

$$\delta\alpha(y) = \delta\Lambda'(\hat{m}(y)) + \Lambda''(\hat{m}(y))\delta\hat{m}(y). \tag{20}$$

Take the differential of (16):

$$\begin{aligned} -\delta\hat{m}(y) &= \tau\delta\beta_A\Lambda(\hat{m}(y)) + \tau\beta_A\Lambda'(\hat{m}(y))\delta\hat{m}(y) + \tau\beta_A\delta\Lambda(\hat{m}(y)) \\ -\delta\hat{m}(y)(1 + \tau\beta_A\alpha(y)) &= \tau\delta\beta_A\Lambda(\hat{m}(y)) + \tau\beta_A\delta\Lambda(\hat{m}(y)). \end{aligned} \tag{21}$$

Plug in (21) into (20) and then into (18):

$$\begin{aligned} \frac{\delta\beta_A}{\beta_A^2}\int \frac{dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} &= \tau\int \frac{\delta\alpha(y)dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} = \\ &= \tau\int \frac{\left(\delta\Lambda'(\hat{m}(y)) + \Lambda''(\hat{m}(y))\delta\hat{m}(y)\right)dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} = \\ &= \tau\int \frac{\left(\delta\Lambda'(\hat{m}(y))\right)dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} - \tau\int \frac{\Lambda''(\hat{m}(y))\left(\tau\delta\beta_A\Lambda(\hat{m}(y)) + \tau\beta_A\delta\Lambda(\hat{m}(y))\right)dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^3\beta_A} \end{aligned}$$

$$\begin{aligned} \delta\beta_A\left[\int \frac{dG(y)}{\left(\tau\alpha(y)\beta_A + 1\right)^2} + \tau^2\int \frac{\Lambda''(\hat{m}(y))\beta_A^2\Lambda(\hat{m}(y))dG(y)}{\left(\tau\alpha(y)\beta_A + 1\right)^3}\right] &= \\ = \tau\int \frac{\delta\Lambda'(\hat{m}(y))dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^2} - \tau^2\int \frac{\Lambda''(\hat{m}(y))\delta\Lambda(\hat{m}(y))dG(y)}{\left(\tau\alpha(y) + 1/\beta_A\right)^3} \end{aligned}$$

We have both $\delta\Lambda$ and $(\delta\Lambda)'$ on the right hand side of the expression above, and we need to have only $\delta\Lambda$. To get it, we will use integration by parts. Consider separately the first term in the previous line:

$$Z_1 := \tau \int \frac{\delta\Lambda'(\hat{m}(y))dG(y)}{(\tau\alpha(y)+1/\beta_A)^2} = \tau\beta_A^2 \int \frac{(\delta\Lambda(\hat{m}(y)))'\, g(y)dy}{(\tau\alpha(y)\beta_A+1)^2} = \tau\beta_A^2 \int \frac{g(y)d\left(\delta\Lambda(\hat{m}(y))\right)}{(\tau\alpha(y)\beta_A+1)^2} =$$

$$= \tau\beta_A^2 \frac{g(y)\delta\Lambda(\hat{m}(y))}{(\tau\alpha(y)\beta_A+1)^2}\Big|_{\underline{y}}^{\overline{y}} - \tau\beta_A^2 \int \delta\Lambda(\hat{m}(y))d\left(\frac{g(y)}{(\tau\alpha(y)\beta_A+1)^2}\right) =$$

$$= -\tau\beta_A^2 \int \delta\Lambda(\hat{m}(y))d\left(\frac{g(y)}{(\tau\alpha(y)\beta_A+1)^2}\right) =$$

$$= -\tau\beta_A^2 \int \delta\Lambda(\hat{m}(y)) \frac{g'(y)\left(\tau\alpha(y)\beta_A+1\right)^2 - 2g(y)\left(\tau\alpha(y)\beta_A+1\right)\tau\beta_A\alpha'(y)}{(\tau\alpha(y)\beta_A+1)^4} dy =$$

$$= \tau\beta_A^2 \int \delta\Lambda(\hat{m}(y))\left[-\frac{g'(y)}{(\tau\alpha(y)\beta_A+1)^2} + \frac{2g(y)\tau\beta_A\alpha'(y)}{(\tau\alpha(y)\beta_A+1)^3}\right] dy$$

Using (19),

$$\alpha'(y) = \Lambda''(\hat{m}(y))\hat{m}'(y).$$

Differentiate (16) wrt y,

$$1 - \hat{m}'(y) = \tau\beta_A\alpha(y)\hat{m}'(y)$$
$$\hat{m}'(y) = \frac{1}{1+\tau\beta_A\alpha(y)}.$$

For brevity, adopt the notation

$$\nu(y) := \frac{1}{1+\tau\beta_A\alpha(y)}.$$

The notation is not coincidental, $\nu(y)$ is equal to the fraction of type-y sellers who are available in equilibrium. Return to compute

$$Z_1 = \tau\beta_A^2 \int \delta\Lambda(\hat{m}(y))\left[-g'(y)\nu(y)^2 + \nu(y)^3 2g(y)\tau\beta_A\Lambda''\nu\right] dy.$$

Now we finish computing the differential $\delta\beta_A$:

$$\frac{\delta\beta_A}{\beta_A^2}\int \frac{dG(y)}{(\tau\alpha(y)+1/\beta_A)^2} =$$

$$= \tau\beta_A^2 \int \delta\Lambda(\hat{m}(y))\left[-g'(y)\nu(y)^2 + \nu(y)^3 2g(y)\tau\beta_A\Lambda''\nu\right] dy - \tau^2 \int \Lambda''(\hat{m}(y))\delta\Lambda(\hat{m}(y))\nu^3\beta_A^3 dG(y) =$$

$$= \tau \int \delta\Lambda(\hat{m}(y))\left[-g'(y)\nu(y)^2\beta_A^2 + \nu(y)^4 2g(y)\tau\beta_A\Lambda''\beta_A^2 - \tau\Lambda''(\hat{m}(y))\nu^3 g(y)\beta_A^3\right] dy.$$

We are interested in the expression in the square brackets in the formula above. Therefore, for some $K>0$ that is constant in y we have:

$$\frac{\delta\beta_A}{\delta\Lambda} = K\left(-g'(y)\nu(y)^2 + \nu(y)^4 2g(y)\tau\beta_A\Lambda'' - \tau\Lambda''(\hat{m}(y))\nu^3 g(y)\beta_A\right) =$$
$$= K\nu(y)^2\left(-g'(y) + g(y)\nu(y)\tau\beta_A\Lambda''(\hat{m}(y))(2\nu(y)-1)\right).$$

□

C Proofs omitted from the Extenstions

Proof of Proposition 6. We need to show that there is a unique solution $(\alpha(y), \beta_A(y))_{y\in Y}$ to $\{(6), (13)\}$, where we treat x as a function of α, as has been determined in lemma Lemma 4.

Use Kakutani theorem. □

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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