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Search, Matching, and Dating Apps: Designed to be
Deleted, or Designed to be Repeated?

Yair Antler Daniel Bird Daniel Fershtman

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Search, Matching, and Dating Apps: Designed to be Deleted, or Designed to be Repeated?*

Yair Antler[†] Daniel Bird[‡] Daniel Fershtman[§]

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Abstract

Should an online matching platform utilize new technologies that enable faster search and better screening of proposed matches? On the one hand, the platform wishes to provide high-quality search and matching services in order to become more attractive to its users; on the other hand, high-quality matches reduce both the duration of search and the likelihood of repeat search, and can therefore reduce revenue from repeated use and advertising exposure. We compare the profits of a matching platform under technologies that differ in search speed and the screening of proposed matches. We find that better technology raises profit when the platform relies mainly on fees paid by users, but can lower profit when advertising revenue is sufficiently important, creating an incentive not to use improved matching capabilities fully.

Keywords: Dating apps, Repeat usage, Learning.

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[†]Corresponding author: Coller School of Management, Tel Aviv University and CEPR. *Email:* yair.an@gmail.com.

[‡]The Eitan Berglas School of Economics, Tel Aviv University. *Email:* dbird@tauex.tau.ac.il.

[§]The Eitan Berglas School of Economics, Tel Aviv University, Emory University, and CEPR. *Email:* danfershtman@gmail.com.

1 Introduction

The rise of online matching platforms has transformed many matching markets. Compared to traditional forms of matchmaking, online platforms can use their technology to reduce both search frictions by creating thick markets and information frictions by using data to identify promising matches. While such technologies can improve the quality of the services that the platform provides to its users, the platform’s incentives need not coincide with its users’ objectives. Users join a platform to find a good match and, ideally, to stop searching; a profit-maximizing platform may instead benefit from continued activity, either through fees paid during repeated search or through advertising exposure.¹

In this paper, we study the incentives of a profit-maximizing matching platform to utilize technologies that make matching more effective: better screening, which improves the expected quality of proposed matches, and faster search, which reduces the time required to meet potential partners. Both improvements make the platform more attractive to its users and increase their willingness to pay for the platform’s services. At the same time, such improvements have a countervailing effect: better screening reduces repeat search by making successful matches more likely, while faster search reduces the time during which the platform can expose its users to advertisements. Thus, online matching platforms face an unusual product-design problem: a better service may reduce profits. We explore under what conditions the utilization of better technology will indeed lead to a reduction in a monopolistic platform’s profits.

To study this question, we develop a platform-mediated search-and-matching model in which the platform earns revenue from fees paid by its users, as well as advertising revenue that is proportional to the time users spend searching.² In our model, users differ in what they regard as a good match (i.e., horizontal differentiation). We represent users’ tastes on a circle, so that the distance between two users measures the fit of their match. The symmetry of the circle gives a simple representation of the platform’s screening technology: the platform proposes only matches whose distance lies below a certain cutoff. Better screening tightens this cutoff and therefore excludes matches with a relatively poor fit.

Users who are matched with one another do not observe their fit immediately, but

¹For examples from online dating, compare Hinge’s claim that it is “designed to be deleted” with allegations that Match Group used technology to keep users “on-app.” See *Oksayan et al. v. Match Group, Inc.*, No. 3:24-cv-00888 (N.D. Cal. filed Feb. 14, 2024).

²We assume that advertising does not directly enter users’ payoffs. However, advertising still affects users indirectly through its impact on the platform’s optimal fee.

instead must infer it through the payoffs they receive while spending time together off the platform. After they learn the fit of their match, they decide whether to break up and return to the platform or remain matched indefinitely. This means that some users become repeat customers. Moreover, as the choice of which matches to terminate is endogenous, the platform’s fee and technology affect not only initial participation but also users’ decisions to return and hence the extent of the platform’s repeat-user base.

Despite the dynamic learning problem and the endogenous repeat search, the framework is tractable. For any given fee and technology, we show that the model admits a unique equilibrium outcome and characterize how the platform’s fee and technology affect users’ search behavior. This equilibrium characterization also enables us to analyze the platform’s pricing problem. We derive an intuitive characterization of the platform’s optimal fees, and provide a condition under which the optimal fee is unique. Moreover, we show that optimal fees decrease as advertising revenue per unit of time spent searching increases, and that zero becomes the unique optimal fee once advertising revenue is sufficiently high.

We then use this characterization to derive the paper’s central technology-comparison result. We find that the platform’s preferences over these technologies depends on how it monetizes its matchmaking services. When advertising revenue per unit of time spent searching is low, the platform can monetize part of the additional value created by better technology, so that better technology yields higher profits. By contrast, when advertising revenue is sufficiently high and users are sufficiently patient, the ranking is reversed: the loss of advertising exposure cannot be offset by fee adjustment or increased demand, and the platform earns less when it operates under the improved technology.

Our formal analysis compares profits across exogenously specified operating regimes and does not endogenize the acquisition or deployment of technological capabilities. The comparison nevertheless has a direct deployment implication when an improved capability nests the baseline regime. If the platform can reproduce the previous screening and meeting process, our analysis identifies an incentive for the platform to retain search and matching frictions that it has the capability to remove.

1.1 Related Literature

The paper is related to the matching-with-search-frictions literature, which explores the properties of equilibrium matching under various assumptions on the search technology,

match payoffs, search costs, the ability to transfer utility, and agents’ rationality. See [Chade, Eeckhout and Smith \(2017\)](#); [Lauermann and Nöldeke \(2025\)](#) for comprehensive reviews of this literature. Specifically, the role of a matchmaker in the marriage market has been studied by [Bloch and Ryder \(2000\)](#), who analyze a model in which a matchmaker can eliminate search frictions. They show that the matchmaker matches agents with partners of their own “caliber,” and that if the matchmaker charges a uniform participation fee, then the more desirable agents are the ones that use the matchmaker’s services. While [Bloch and Ryder \(2000\)](#) were the first to study the effects of matchmakers on matching markets, they did not study the matchmaker’s incentives, how those incentives depend on technology, or how they shape matching-market outcomes.

Contemporaneous work by [Giesemann \(2025\)](#) studies the platform’s choice of a matching rule when it has complete information about the users’ types. She shows that a platform may delay matching or select an inefficient matching rule. Her research complements this paper that studies how improvements in screening and search speed affect pricing and profits when users learn match quality off the platform and may subsequently return.

Within the literature on marriage markets, [Chade \(2006\)](#) and [Antler, Bird and Fershtman \(2026\)](#) incorporate a learning aspect into their models.³ [Chade \(2006\)](#) assumes that upon meeting, agents observe a noisy signal about one another’s type, and learn the truth in the following period. He shows that this leads to an “acceptance curse” whereby prospective partners that are willing to match appear more attractive than they actually are. [Antler, Bird and Fershtman \(2026\)](#) explore the effects of pre-match learning on equilibrium and socially efficient sorting.

In studying the implications of technological improvements on two-sided search markets, this paper is related to [Adachi \(2003\)](#), [Lauermann and Nöldeke \(2014\)](#), and [Antler and Bachi \(2022\)](#), all of which study the effects of reductions in search frictions. Unlike the present paper, these papers focus on the frictionless limit. Moreover, these papers focus only on technological changes that improve the speed of search, but do not consider changes that impact the screening of proposed matches. Furthermore, these papers do not take the platform’s pricing decisions into account.

Markets where agents purchase access to one another are the focus of a vast literature on two-sided markets.⁴ Much of this literature abstracts from the process by which plat-

³Within the more general matching-with-search-frictions literature, [Jovanovic \(1984\)](#) and [Moscarini \(2005\)](#) incorporate a learning aspect into a two-sided search model to study the effect of post-match learning on employee turnover.

⁴See [Belleflamme and Peitz \(2021\)](#) and [Jullien, Pavan and Rysman \(2021\)](#) for recent overviews.

form users are paired. A growing platform-design literature instead studies how platforms shape users’ choice sets, search actions, information, and access. [Halaburda, Piskorski and Yildirim \(2018\)](#) show that a restricted-choice online dating platform can charge higher prices and coexist with a platform that offers more matching options. [Basu, Bhaskaran and Mukherjee \(2019\)](#) jointly analyze search, authentication quality, market positioning, and pricing. More recently, [Basu, Bhaskaran and Mukherjee \(2024\)](#) study services that assess horizontal compatibility and authenticate vertical quality, and show that stronger counseling capability need not increase platform revenue. [Kanoria and Saban \(2021\)](#) show that restricting which side may initiate contact and hiding information about partner quality can reduce wasteful search and improve welfare.

Relative to this platform-design literature, our analysis focuses on post-match feedback: better matching changes whether users terminate realized relationships and return to search, thereby affecting the endogenous repeat-customer base. Consequently, we study how the platform’s fee and matching technology jointly determine initial participation, relationship termination, repeat search, advertising exposure, and platform profit.⁵

The incentives created by the possibility of future sales have also been studied in other contexts. An extensive literature shows how firms can signal their quality in an initial period to attract more consumers or charge higher prices in subsequent periods (see, e.g., [Milgrom and Roberts, 1986](#); [Bagwell and Riordan, 1991](#)). Perhaps closer to our setting is the literature on planned obsolescence in durable goods markets (see, e.g., [Levhari and Srinivasan, 1969](#); [Schmalensee, 1970](#); [Swan, 1972](#)). In this strand of the literature, firms trade off current demand and the possibility of enlarging their repeat-customer base by choosing the durability of their good. In such markets, durability is exogenous in the eyes of consumers, who purchase again once the product stops working. By contrast, in our matching model, the decision to return is endogenous from the customers’ perspective. Customers decide whether they consider a match acceptable, and this decision trades off the attractiveness of their current match with the attractiveness of rejoining the platform in search of new partners, where the latter is determined by the quality of the platform’s services.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 characterizes agents’ equilibrium behavior for a given fee and technology, and studies

⁵A related literature studies how consumers’ search behavior is shaped by the presence of a search engine influencing the search pool; see, e.g., [Eliaz and Spiegel \(2016\)](#), [Hagi and Jullien \(2011\)](#), [White \(2013\)](#), and [De Corniere \(2016\)](#). In a related advertising context, [Fainmesser and Galeotti \(2021\)](#) study the tradeoff between paid endorsements and follower engagement.

how this behavior depends on the platform’s technology and fee. Section 4 analyzes the platform’s pricing problem and compares profits across alternative search-and-matching technologies. Section 5 concludes.

2 The Model

We study an environment in which a monopolistic platform facilitates matching between two sets of agents, which we sometimes refer to as men and women. We assume that the two sets are symmetric. The market operates in continuous time, and agents discount the future at a rate of $r > 0$. New agents enter each side of the market at a constant rate of $\eta > 0$ and draw an outside option $u_o \sim F(\cdot)$. The heterogeneity in outside options can reflect competition with other (differentiated) platforms. The distribution of the outside option has support on $[0, 1/r]$ and admits a strictly positive and differentiable density $f(\cdot)$.⁶

Agents are horizontally differentiated, that is, each agent has idiosyncratic preferences over potential partners. We assume that the distribution of these preferences is independent of the distribution of the outside option. To impose some structure on the model, we borrow Salop’s (1979) model of horizontal differentiation and assume that, on each side of the market, agents’ tastes are uniformly distributed on a circle with circumference 1. We identify each agent by their (clockwise) distance from the top of the circle. The length of the arc between two agents determines the *fit* of their match: the shorter the arc, the better the fit. Agents do not observe their fit upon meeting one another.

Search-and-matching technology. Based on its information, the platform can partially predict the fit of potential matches. In particular, for any couple $\langle x, y \rangle$, the platform can identify whether $\alpha(x, y) \leq \theta_0$, where $\alpha(x, y)$ denotes the length of the (shortest) arc between x and y . The platform uses this information to screen matches: it restricts agents’ meetings to matches that have a (sufficiently) good fit, that is, for which $\alpha(x, y) \leq \theta_0$. We refer to $\theta_0 \in (0, 1/2)$ as the level of screening provided by the platform; note that a lower value of θ_0 is associated with better screening.

Search on the platform is time-consuming. Each agent on the platform randomly meets partners who pass the platform’s screening at a constant rate of μ (i.e., the matching technology is linear). Since the fit of a match is unobservable, all proposed matches are

⁶As will become apparent below, the expected utility from joining the platform is strictly less than $1/r$. Hence, there is no loss of generality in imposing this upper bound on the outside option.

ex-ante symmetric. Hence, agents who choose to join the platform will leave the platform with their first proposed partner (who simultaneously leaves the platform).⁷

Payoffs and learning. Utility in our model is nontransferable and the flow payoff while searching for a match on the platform is normalized to zero.⁸ We consider a setting where the flow payoff from a relationship is higher for better-fitting matches and increases with relationship duration. Such payoff processes capture a natural idea: the better one knows one’s partner, the greater the benefit one derives from the relationship. For instance, a couple’s mutual trust may increase over time (which results in a greater payoff) or they may benefit from exploring new joint activities and “fine-tuning” their relationship until it realizes its potential, which is captured by the couple’s fit.

In our model, agents must infer the fit of a match based on their flow payoffs. This dynamic inference problem presents a modeling challenge due to the infinite state space. We introduce a payoff structure that enables closed-form updating rules while capturing the natural feature mentioned above. Specifically, we assume that the flow payoff to an agent in a couple with fit α that has been together for τ units of time is

$$u(\alpha, \tau) = 1 - \beta \cdot \max\{\alpha, \theta_\tau\},$$

where θ_τ evolves according to

$$\frac{d\theta_\tau}{\theta_\tau} = -\lambda d\tau, \tag{1}$$

where the initial condition for this process is the platform’s level of screening θ_0 . The parameter $\lambda > 0$ governs the rate at which a couple’s payoff increases over time, while the parameter $\beta > 0$ measures the importance of fit.

If a couple has been together for τ units of time and their flow payoff has increased during all their time together, they will infer that $\alpha \leq \theta_\tau$. On the other hand, if their flow payoff has become constant at $\hat{\tau} < \tau$, they will infer that $\alpha = \theta_{\hat{\tau}}$. Figure 1 depicts the dynamics of learning for a couple whose tastes are represented by the blue and red dots. Upon being matched, the agents infer that $\alpha \leq \theta_0$; after being together for 1 unit of time they infer that $\alpha \leq \theta_1$; and after spending 2 units of time together they learn the value of α .

⁷The assumption that agents leave the platform with the first proposed match is an artifact of the assumption that all the screening is done by the platform. Indeed, our model is equivalent to one in which the platform provides information to the agents, who then screen potential matches on their own. The only difference is that in such a model the effective meeting rate would be $\hat{\mu} = 2\theta_0\mu$.

⁸We explain why our results continue to hold under transferable utility in Online Appendix B.

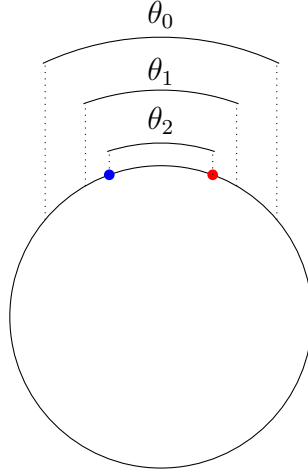


Figure 1: Learning technology.

Throughout the paper, we impose two qualitative assumptions. First, we assume that an agent would rather be single than be matched to a partner with the worst feasible fit. Second, to make the problem nontrivial, we assume that the expected discounted value of a match drawn through the platform is positive. The former assumption is captured by the parametric restriction

Assumption 1 $\beta\theta_0 > 1$,

and the latter is captured by

Assumption 2

$$\int_0^{1/\beta} \frac{1}{\theta_0} \left(\int_0^\infty e^{-r\tau} u(\alpha, \tau) d\tau \right) d\alpha + \int_{1/\beta}^{\theta_0} \frac{1}{\theta_0} \left(\int_0^{\log\{\theta_0/\alpha\}/\lambda} e^{-r\tau} u(\alpha, \tau) d\tau \right) d\alpha > 0.$$

The first integral is the expected discounted value of a match for which the eventual match payoff is positive ($\alpha \leq 1/\beta$), so that the agent would continue the match indefinitely if they did not have the option to return to the platform to search again. The second integral is the expected discounted value of a match that the agent terminates when the fit is revealed ($\alpha > 1/\beta$).⁹

The platform in our model generates revenue from two sources: an endogenously determined fee that it charges its users, and an exogenous flow of advertising revenue

⁹ $\log\{\theta_0/\alpha\}/\lambda$ is the amount of time it takes the agent to learn that the fit of a match is exactly α . See Equation (A.1) for a formal derivation.

that it obtains from exposing each of its active users to advertisements. We denote the flow of advertising revenue per active user by $A \geq 0$. We interpret A as the platform’s revenue from a fixed amount of advertising exposure, rather than as the quantity or intrusiveness of advertisements shown to users. Thus, changes in A may reflect changes in advertiser demand, advertising prices, or targeting effectiveness while holding the user experience fixed. Moreover, we assume that this fixed exposure does not enter agents’ utility.¹⁰

Strategies. The platform’s objective is to maximize its profit (we derive the profit function in Section 4). Its strategy specifies a fee, $\phi \geq 0$, which agents pay when they join or rejoin the platform. In practice, platforms often charge periodic subscription fees. For a fixed technology, the relevant object for users’ participation and return decisions is the expected discounted value of the payments made during each round of search, which can be represented by an equivalent lump-sum fee. Because users evaluate future payments in discounted utility terms whereas the platform’s steady-state objective records their contribution to revenue flow, this representation does not in general preserve both users’ payment costs and the platform’s receipts from a given periodic fee. We therefore take lump-sum fees per round of search as primitive and abstract from the timing of payments.

Each agent’s strategy specifies two objects: the conditions under which to unilaterally terminate an existing match and whether to join the platform in the first place. Since the setting is stationary, an agent who terminates a match after joining the platform will optimally rejoin rather than reverting to their outside option. Hence, we do not formally specify the rejoining decision.

As in many other two-sided matching models, the agents’ ability to unilaterally terminate a match can sustain a plethora of equilibria in which agents choose to separate from their partner on the basis of a belief that the partner will choose to separate from them. To abstract away from equilibria that arise from such a lack of coordination, the matching-with-search-frictions literature (e.g., [Burdett and Coles, 1997](#); [Smith, 2006](#)) typically assumes that agents accept any match that exceeds their reservation value; that is, agents decide which matches to accept as if their choice were pivotal. In this paper, we make the analogous assumption that agents’ termination choices are made as if they were pivotal.

¹⁰In some cases, agents may benefit from being exposed to personalized advertisements. See, e.g., [Bird and Neeman \(2025\)](#) and the references therein. We abstract from the platform’s choice of advertising load and from any nuisance cost generated by additional advertisements.

We focus on strategies that are symmetric across agents and stationary. Agents in our model are ex-ante symmetric. If they use symmetric strategies, then the distribution of agents that are active on the platform remains uniform at all points in time. This has two key implications. First, agents are also interim symmetric, which justifies their use of symmetric strategies throughout the dynamic interaction. Second, a couple that has been together for τ units of time without learning their fit believes that their fit is distributed uniformly on $[0, \theta_\tau]$.

Threshold strategies. Because θ_τ strictly decreases over time, a couple's flow payoff $u(\alpha, \tau)$ (and therefore their expected continuation payoff) strictly increases until their fit is revealed. By contrast, the value of terminating a match and rejoining the platform does not change over time. It follows that the continuation value of staying in a match of unknown fit, relative to the value of terminating the match and returning to the platform, increases over time until the couple's fit is revealed. Therefore, the only time at which an agent may find it optimal to terminate a match is when its fit is revealed.¹¹ Furthermore, if agent x prefers staying in a match with agent y to terminating the match (when its fit is revealed), agent x would prefer to stay with every agent y' such that $\alpha(x, y') < \alpha(x, y)$. The following lemma is implied:

Lemma 1 (Threshold Strategies) *Agents' optimal separation strategies can be represented by a separation threshold $\alpha_s \in [0, \theta_0]$ such that*

1. *Agents remain together until they learn their fit.*
2. *Upon learning their fit, they terminate the match if $\alpha(x, y) > \alpha_s$, and remain together indefinitely if $\alpha(x, y) \leq \alpha_s$.*

Figure 2 depicts how the strategy of an agent located at the top of the circle determines the outcome of matches with various partners: a match with a partner whose location lies in the “Successful” region leads to an indefinite relationship, whereas a match with a partner in either “Unsuccessful” region leads to eventual separation and a return to the platform. Potential partners on the arc of the “Not Matched” region are screened away by the platform.

The agents' choice of whether to join the platform is straightforward. An agent will join the platform if and only if their outside option is less than their expected value from

¹¹Immediate termination of the match is also suboptimal since all matches are ex-ante symmetric and the expected utility from a single match is positive (Assumption 2).

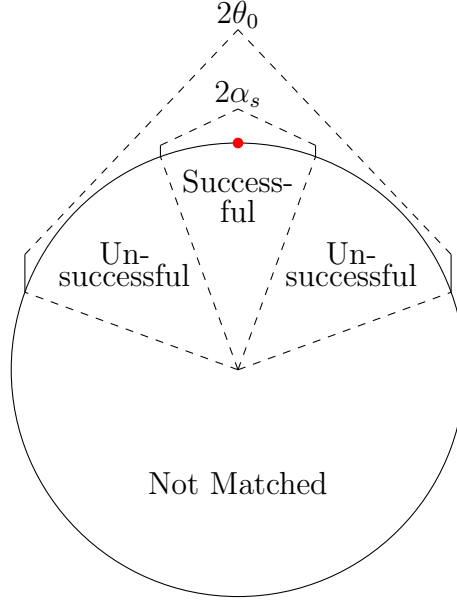


Figure 2: Strategies and outcomes.

optimal search at a cost of ϕ per round of search. Hence, agents will join the platform if and only if their outside option is less than a cutoff u_o^* , and so the probability that a newly arriving agent joins the platform is $F(u_o^*)$.

Equilibrium. Agents' optimal separation choices depend on the value of rejoining the platform. Given the linearity of the matching technology and the fact that agents use stationary symmetric strategies, this value depends only on $\langle \mu, \theta_0, \phi \rangle$. We say that the agents' strategy, $\langle \alpha_s^*, u_o^* \rangle$, constitutes a *continuation equilibrium* if α_s^* maximizes the agents' expected discounted payoff given $\langle \mu, \theta_0, \phi \rangle$, and agents with $u_o \leq u_o^*$ find it optimal to join the platform. We say that $\langle \phi^*, \alpha_s(\phi), u_o(\phi) \rangle$ is an *equilibrium* if $\langle \alpha_s(\phi), u_o(\phi) \rangle$ is a continuation equilibrium for every $\phi \geq 0$, and ϕ^* maximizes the platform's expected profit given $\langle \alpha_s(\cdot), u_o(\cdot) \rangle$.

3 Agents' Behavior

In this section, we analyze the agents' behavior on the platform, taking the fee and matching technology as given. We show that there exists a unique continuation equilibrium and characterize it in closed form. We then study how equilibrium behavior responds to technological changes.

3.1 Agents' Behavior on the Platform

The continuation equilibrium in our model can be of two types: a *nontrivial equilibrium* in which a strictly positive mass of agents join the platform or a *trivial equilibrium* in which no agent finds it uniquely optimal to join. In a nontrivial equilibrium, the assumption that $\beta\theta_0 > 1$ implies that agents terminate matches with positive probability. Moreover, since the problem is stationary, after terminating a match an agent will pay the fee to rejoin the platform (rather than revert to the outside option). In what follows, we characterize the nontrivial equilibria. After doing so, we show that there exists a threshold $\bar{\phi}$ such that the equilibrium is nontrivial if and only if $\phi < \bar{\phi}$.

For an agent in a couple $\langle x, y \rangle$ that has learned its fit is $\alpha(x, y)$, the continuation value of remaining in the relationship indefinitely is

$$\frac{1 - \beta\alpha(x, y)}{r}.$$

Denote by W_s the (endogenous) continuation value for an agent that is on the platform. In a nontrivial equilibrium the continuation value after terminating a match is $W_s - \phi \geq 0$. The equilibrium separation threshold α_s is the fit level α for which the agents are indifferent between staying together and terminating their match to rejoin the platform. Thus, in a nontrivial equilibrium, it must be that

$$\frac{1 - \beta\alpha_s}{r} = W_s - \phi.$$

Lemma 2 (Equilibrium strategies) *In a nontrivial equilibrium, the separation threshold satisfies*

$$\alpha_s = \frac{1 - r(W_s - \phi)}{\beta}, \tag{2}$$

and $\alpha_s \in (0, 1/\beta)$.

To characterize the agents' equilibrium behavior, we connect W_s to the separation threshold derived in Lemma 2 using a recursive representation of W_s . In a nontrivial equilibrium, each match either lasts indefinitely or eventually ends, after which the agents return to the platform. We refer to the former type of match as a *successful match* and to the latter type of match as an *unsuccessful match*. A match between agents x and y is successful if $\alpha(x, y) \leq \alpha_s$ and is unsuccessful otherwise. Denote the probability that a match is successful by γ .

For $i \in \{s, n\}$, where s represents a successful match and n represents an unsuccessful one, let EV_i denote the expected payoff generated by the current match. Note that EV_s is the continuation value after a successful match, whereas EV_n includes the payoff obtained while a couple remains together net of the discounted cost of rejoining the platform, but does not include the payoffs obtained from future relationships. Let σ denote the expected discount factor at the end of an unsuccessful match (relative to its starting point). The continuation value for an agent that is on the platform can be written recursively as

$$W_s = \frac{\mu}{\mu + r} ((1 - \gamma) (EV_n + \sigma W_s) + \gamma EV_s), \quad (3)$$

where $\frac{\mu}{\mu + r}$ is the expected discount factor until the agent receives their first proposed match. Using this representation, we establish that there exists a unique continuation equilibrium and derive a critical level $\bar{\phi}$ such that this equilibrium is nontrivial if and only if $\phi < \bar{\phi}$. This critical level equates the agent's expected utility from paying the fee to search (once) for a new partner with the lower bound of the outside option, namely, zero. Let $\xi \equiv \frac{r}{\lambda}$.

Proposition 1 *For any given ϕ , there exists a unique continuation-equilibrium outcome. This continuation equilibrium is nontrivial if and only if*

$$\phi < \mu \frac{1 - \xi(\beta\theta_0)^{\xi+1} (\beta\theta_0(\xi + 1) - (\xi + 2))}{\theta_0^{\xi+1} \beta^{1+\xi} (\xi + 1)(\xi + 2)r(\mu + r)} \equiv \bar{\phi}. \quad (4)$$

The nontrivial continuation equilibrium (when it exists) is characterized by

$$\frac{\xi^2 + 2\xi}{\theta_0} (\lambda\xi + \lambda + \mu)\alpha_s^* + \frac{\mu}{\theta_0^{\xi+2}} (\alpha_s^*)^{\xi+2} = \mu\xi(\xi + 1) + \frac{\xi(\xi + 2)(\lambda(\xi + 1)(\lambda\xi\phi + \mu\phi + 1))}{\theta_0\beta}, \quad (5)$$

and $u_o^* = \frac{1 - \beta\alpha_s^*}{r}$.

While the continuation-equilibrium outcome is unique, the continuation equilibrium itself need not be unique when it is a trivial equilibrium. In such cases, all separation thresholds are vacuously optimal as agents do not join the platform.

By Assumption 2, the expected value of search is strictly positive if $\phi = 0$. Therefore,

Assumption 2 is equivalent to the parametric restriction $\bar{\phi} > 0$, that is,

$$1 - \xi(\beta\theta_0)^{\xi+1} (\beta\theta_0(\xi + 1) - (\xi + 2)) > 0. \quad (6)$$

Note that, fixing all other parameters, this inequality will hold if agents are sufficiently patient, i.e., if $\xi = r/\lambda$ is small enough.

3.2 Agents' Responses to Changes in Matching Technology

The closed-form characterization of the continuation equilibrium enables us to derive comparative statics for the agents' behavior. Such comparative statics are not only of interest in their own right, but also play a key role in the sequel when we study how the platform's profits and pricing change with its technology.

Recall that the agents' separation threshold equates the value of remaining with a marginally acceptable partner, $\frac{1-\alpha_s^*\beta}{r}$, to the value of terminating the match and returning to the platform, $W_s - \phi$. Thus, improvements in the platform's technology that raise W_s — whether through an increase in μ or a reduction in θ_0 — strengthen an agent's incentive to terminate a match and return to the platform. Similarly, a reduction in the platform's fee also increases agents' incentives to return to the platform and search for better matches.

The agent's separation threshold also affects the *conversion rate*

$$\gamma \equiv \Pr(\alpha \leq \alpha_s^* \mid \alpha \leq \theta_0) = \frac{\alpha_s^*}{\theta_0},$$

which is the probability that a match is successful. While this object is not of direct interest to the agents, it is central to the platform's profits as it determines the extent of repeat use. Faster search and lower fees make agents more selective about which relationships to continue without affecting the distribution of proposed-match quality. Thus, such changes reduce the conversion rate. On the other hand, better screening reduces the set of successful matches, but also improves the fit of proposed matches. We show that the latter force dominates, so that better screening increases the conversion rate. Formally, we have the following result.

Lemma 3 *Within the parameter region in which the nontrivial continuation equilibrium exists,*

1. *The separation threshold is increasing in ϕ and θ_0 , and decreasing in μ .*

2. The conversion rate is increasing in ϕ , and decreasing in μ and θ_0 .

4 The Platform

We now study the platform's pricing problem, namely, maximizing the expected profit while taking the agents' equilibrium behavior into account. We then study the impact of technological changes on the platform's profits.

4.1 The Platform's Pricing Problem

In order to analyze the platform's pricing problem, we first derive its steady-state profit flow. Agents enter each side of the market at the constant rate η . Hence, in a stationary environment, the platform's aggregate profit flow equals 2η times the expected total revenue generated by a newly arriving agent. Since the factor 2η is independent of the platform's fee, maximizing steady-state profit is equivalent to maximizing expected revenue per newly arriving agent.¹² Furthermore, by Proposition 1, agents join the platform with probability zero if $\phi \geq \bar{\phi}$, and so, for such fees, the platform's profit is zero. Hence, without loss of generality, we can restrict the platform's choice of fee to $[0, \bar{\phi}]$.¹³

The probability that a new agent joins the platform is $F(W_s(\phi) - \phi)$, where $W_s(\phi)$ is the continuation value of the platform's users as a function of ϕ . Let $D(\phi) \equiv F(W_s(\phi) - \phi)$ denote the "demand" for the platform's service from new agents as a function of ϕ . By Equation (2) the value of joining the platform is $W_s(\phi) - \phi = \frac{1 - \beta\alpha_s(\phi)}{r}$. Thus, we have that

$$D(\phi) = F\left(\frac{1 - \beta\alpha_s(\phi)}{r}\right),$$

where $\alpha_s(\phi)$ denotes the solution to (5) as a function of ϕ .¹⁴

In a nontrivial equilibrium, users that initially join the platform do so (in expectation) more than once. Thus, the platform's profit depends on the size of its repeat-customer base. This size, in turn, depends on the conversion rate of proposed matches. Let $\gamma(\phi) = \frac{\alpha_s(\phi)}{\theta_0}$ denote the equilibrium conversion rate of matches as a function of ϕ . On average,

¹²The same objective is obtained if the platform discounts future profits at any positive rate and the market is evaluated in steady state: the present value of a constant steady-state profit flow is proportional to that flow.

¹³This problem is nondegenerate since, by Assumption 2, $\bar{\phi} > 0$.

¹⁴As there is a unique continuation equilibrium for any fixed $\phi < \bar{\phi}$ (Proposition 1), this function is well defined.

an agent is matched with $\frac{1}{\gamma(\phi)}$ partners, and so the expected volume of search generated by each new agent is

$$V(\phi) = \frac{D(\phi)}{\gamma(\phi)}.$$

The platform's expected profit per round of search is $\phi + A/\mu$. Thus its expected profit per newly arriving agent is $\pi(\phi) = V(\phi)(\phi + A/\mu)$, and the platform's objective is

$$\max_{\phi \in [0, \bar{\phi})} V(\phi)(\phi + A/\mu). \quad (7)$$

Proposition 2 *The platform's problem has at least one solution, and any interior optimal fee satisfies the first-order condition*

$$V(\phi) = \left(\frac{\alpha'_s(\phi)}{\alpha_s(\phi)} V(\phi) - \frac{D'(\phi)}{\gamma(\phi)} \right) (\phi + A/\mu). \quad (8)$$

Furthermore, there exists $\underline{k}$ such that the optimal fee is unique if

$$-\frac{d^2}{du_o^2} \log \left(\frac{F(u_o)}{1 - ru_o} \right) \geq \underline{k} \frac{d}{du_o} \log \left(\frac{F(u_o)}{1 - ru_o} \right), \quad (9)$$

for all $u_o \in (0, W_s(0))$.

The first-order condition (8) captures the central tradeoff that arises in a dynamic setting where the platform's pricing decisions determine both the probability that agents initially join the platform and the probability that they return to the platform. The left-hand side captures the marginal gain from increasing the fee: a marginal increase in ϕ raises revenue in proportion to the volume of search. The right-hand side captures the marginal loss through both initial demand and repeat usage: Increasing the fee reduces demand, and, moreover, this loss is multiplied by the fact that each new agent searches more than once. This effect is captured by the term $-D'(\phi)/\gamma(\phi)$. In addition, increasing the fee reduces repeat search by the platform's existing customer base. This effect is captured by the term $\frac{\alpha'_s(\phi)}{\alpha_s(\phi)} V(\phi)$.

Uniqueness is a curvature statement. Because the equilibrium response $\alpha_s(\phi)$ is endogenous, the expected revenue per user $(\phi + A/\mu)/\gamma(\phi)$ need not be concave in ϕ (as is the case in standard monopoly pricing problems where revenue per client is simply ϕ). Thus, a standard assumption that demand is log-concave need not suffice to obtain a unique optimum. A sufficient condition for a unique optimum is that $\log D(\phi)$ be suffi-

ciently concave to overcome any potential convexity in the expected revenue from each user. Nevertheless, the economic interpretation of this condition is the same as that of a standard log-concavity assumption: it implies that the reverse hazard rate must decrease sufficiently fast as agents' utility from joining the platform rises. Uniqueness of the optimal fee, together with smoothness of the profit function, also ensures that optimized profit is differentiable in the technology parameters, which will be useful below.

The sufficient condition for uniqueness is nonvacuous for familiar outside-option distributions. For example, normalize $r = 1$ and suppose that the outside option is uniformly distributed on $[0, 1]$. In this case, Condition (9) holds whenever

$$\frac{1 - 2W_s(0)}{W_s(0)(1 - W_s(0))} \geq \underline{k},$$

and hence whenever $W_s(0)$ is sufficiently below one-half.

4.1.1 Optimal Pricing and Advertising Revenue

Optimal pricing depends on advertising revenue in a simple way. Advertising revenue is earned in proportion to the volume of search, and higher fees reduce volume by lowering entry and by reducing the probability that users return to the platform after an unsuccessful match. Thus, as advertising revenue becomes more important, the platform has a stronger incentive to increase search volume. The next result formalizes this force and shows that a zero-fee business model arises endogenously once advertising revenue per user is sufficiently large.

Let

$$\Phi^*(A) \equiv \arg \max_{\phi \in [0, \bar{\phi})} V(\phi) \left(\phi + \frac{A}{\mu} \right)$$

denote the nonempty set of optimal fees at advertising revenue A .

Proposition 3 *Let $A_2 > A_1$. For every $\phi_i \in \Phi^*(A_i)$, $i = 1, 2$,*

$$\phi_2 \leq \phi_1,$$

where the inequality is strict when $\phi_1 > 0$. Moreover, there exists $A^\dagger(\theta_0, \mu) \in (0, \infty)$ such

that

$$\begin{aligned} A < A^\dagger(\theta_0, \mu) &\implies 0 \notin \Phi^*(A), \\ A = A^\dagger(\theta_0, \mu) &\implies 0 \in \Phi^*(A), \\ A > A^\dagger(\theta_0, \mu) &\implies \Phi^*(A) = \{0\}. \end{aligned}$$

4.2 The Effect of Technological Changes on the Platform's Profits

We now explore the implications of technological advances for the platform's profits. In what follows, a technology specifies the screening and meeting processes that govern the platform's service, rather than the set of such processes from which the platform could choose.

First, consider the effect of better screening (i.e., lower θ_0). Better screening does not impact the platform's advertising revenue per round of search, and the envelope theorem logic implies that the impact of re-optimizing the fee is of second order. It follows that the effect of better screening on the platform's profits is driven entirely by its effect on the volume of search. By Lemma 3, better screening increases the conversion rate, and thereby reduces repeat use. On the other hand, better screening increases the expected utility from joining the platform, and thus attracts more consumers. Thus, better screening has an ambiguous effect on volume.

Next, consider faster search. Faster search has a clear positive impact on the platform's volume: not only does it increase demand by increasing the agents' expected utility from joining the platform, but it also increases repeat use of the platform by decreasing the conversion rate. However, faster search also has a negative effect in that it decreases the advertising revenue per round of search. By the same envelope theorem logic, whether faster search increases profits depends on whether the increase in volume offsets the loss in advertising revenue.

Let $V(\phi; \theta_0, \mu)$ denote the volume as a function of the fee and technology, and let $\phi^*(\theta_0, \mu, A)$ denote the unique optimal fee as a function of technology and advertising revenue when the condition for uniqueness of the optimal fee ((9)) holds.

Proposition 4 *Suppose that Condition (9) holds.*

1. *A marginal improvement in screening reduces profits if and only if*

$$\left. \frac{\partial V(\phi; \theta_0, \mu)}{\partial \theta_0} \right|_{\phi=\phi^*(\theta_0, \mu, A)} > 0. \quad (10)$$

2. A marginal increase in the speed of search reduces optimal profits if and only if

$$\left. \frac{\partial V(\phi; \theta_0, \mu)}{\partial \mu} \right|_{\phi=\phi^*(\theta_0, \mu, A)} \left(\phi^*(\theta_0, \mu, A) + \frac{A}{\mu} \right) < \frac{A}{\mu^2} V(\phi^*(\theta_0, \mu, A); \theta_0, \mu). \quad (11)$$

The interpretation of Condition (10) is straightforward: since better screening is a reduction in θ_0 , the condition states that improved screening increases search volume. Condition (11) compares the marginal value of increased volume (the LHS) with the marginal reduction in advertising revenue (the RHS).

The preceding analysis identified mechanisms by which technological improvements may either increase or reduce the platform's profit and provided intuitive economic conditions under which better technology reduces profits. However, that analysis did not provide testable conditions under which this occurs. We now show that the platform's profit ranking across alternative technologies is inherently connected to the relative importance of its sources of income: platforms that generate revenue mainly through fees earn more under improved technology, whereas platforms that rely heavily on advertising revenue may earn less.

To gain intuition for the first result, consider the case where the advertising revenue is zero. In this case, basic economic intuition suggests that better technology will increase demand and thus increase profits even if the platform does not adjust its fee. Indeed, if the rate of search increases, both initial demand and repeat usage increase, and so the entire profit curve shifts up.

Better screening has a more subtle effect because its effect on search volume is ambiguous: demand increases, but repeat use decreases. To resolve this ambiguity, assume that, following an improvement in screening, the platform increases its fee to maintain the same separation threshold. That is, the platform maintains the same demand. In this case, the impact of better screening on profits boils down to the question of whether the aforementioned increase in fee is enough to offset the reduction in repeat usage due to better screening. The key step in the next result is to show that this is indeed the case.

Let

$$\pi^*(\theta_0, \mu, A) \equiv \max_{\phi \in [0, \bar{\phi})} V(\phi; \theta_0, \mu) \left(\phi + \frac{A}{\mu} \right)$$

denote profit under technology $\langle \theta_0, \mu \rangle$ and advertising revenue A .

Proposition 5 *Consider a baseline technology $\langle \theta_0, \mu \rangle$ and an improved technology $\langle \theta'_0, \mu' \rangle$*

such that

$$\theta'_0 \leq \theta_0, \quad \mu' \geq \mu,$$

with at least one inequality strict. Suppose that both technologies satisfy Assumptions 1 and 2. There exists $\underline{A} > 0$ such that, for every $A \in [0, \underline{A}]$,

$$\pi^*(\theta'_0, \mu', A) > \pi^*(\theta_0, \mu, A).$$

Proposition 5 establishes that when advertising revenue is small, technological improvements raise profits. That is, the platform can monetize the increase in the value of the service provided to its users.

We now show that this conclusion is reversed when advertising revenue is large and agents are patient. The key observation is that, by Proposition 3, sufficiently large advertising revenue induces the platform to set a zero fee. In that regime, the platform's profit is proportional to the amount of time users spend searching on the platform. Moreover, better technology reduces profits by helping users resolve their search more efficiently, thereby reducing the amount of monetizable activity they generate.

We formally derive this result in the patient-agent limit. To vary patience without changing the normalized distribution of outside options, define

$$z \equiv ru_o \in [0, 1].$$

As r varies, let the distribution of z be fixed and denote it by G ; we assume that G has a strictly positive differentiable density on $[0, 1]$. Let $V_r(\phi; \theta_0, \mu)$ denote search volume as a function of the agents' discount rate r , and let

$$\Pi_r^*(\theta_0, \mu, A) \equiv \max_{\phi \in [0, \phi)} V_r(\phi; \theta_0, \mu) \left(\phi + \frac{A}{\mu} \right)$$

denote profit as a function of r .

Proposition 6 *Consider a baseline technology $\langle \theta_0, \mu \rangle$ and an improved technology $\langle \theta'_0, \mu' \rangle$ such that*

$$\theta'_0 \leq \theta_0, \quad \mu' \geq \mu,$$

with at least one inequality strict. Suppose that both technologies satisfy Assumption 1. There exists $\bar{r} > 0$ such that, for every $r \in (0, \bar{r})$, there exists $\bar{A}(r) < \infty$ such that, for

every $A \geq \bar{A}(r)$,

$$\Pi_r^*(\theta'_0, \mu', A) < \Pi_r^*(\theta_0, \mu, A).$$

Proposition 6 uses the patient-agent limit and the high-advertising region to isolate the mechanism through which better technology can reduce profits. When advertising revenue is sufficiently high, the optimal fee is zero, so the profit comparison is driven directly by the amount of monetizable search activity generated under each technology. The following example shows that the same force can reverse the profit ranking even when the platform charges a strictly positive fee.

Example 1 Fix $r = 0.01, \lambda = 2, \mu = 0.5, \beta = 4, A = 1.5$, and assume that the outside option is distributed via the CDF

$$F(u_o) = 0.4(ru_o) + 0.6(ru_o)^{20}.$$

Maximizing $\pi(\phi)$ numerically yields: $\phi^* \approx 3.187$ and $\pi^* \approx 6.203$ for $\theta_0 = 0.4$; and $\phi^* \approx 5.813$ and $\pi^* \approx 5.892$ for $\theta_0 = 0.3$. Thus, better screening reduces profits even though the platform charges a positive fee in both cases.

5 Concluding Remarks

In this paper, we shed light on the incentives of profit-maximizing platforms to utilize technologies that improve matching by comparing the profits of a matching platform under different technologies. The model distinguishes between two dimensions of technology: the speed with which users meet potential partners and the level of screening of proposed matches. Both improvements make the platform more valuable to users, but they also change the amount of search activity generated by each user. This creates a potential conflict between users and the platform. When the platform relies mainly on user fees, it can monetize the additional value created by better technology, and technological improvements raise profits. However, when the platform relies heavily on advertising revenue, the conclusion can be reversed: better technology reduces monetizable search activity and can lower the platform's profit.

One of the main contributions of this paper is a tractable model of search, matching, learning and separation. We use it to study the incentives of dating apps to adopt new technologies. However, the model has additional applications. For example, it can be

used to study divorce-related trends. To this end, we can interpret ϕ as a divorce cost that couples must incur to go back to the singles market and study how changes in divorce costs and the matching process affect divorce rates in different countries.

Pricing, Profits, and Technology

A natural conjecture is that when a monopolistic platform improves its technology, it will raise its fee in order to capture the additional surplus created by the improvement. This conjecture is not generally correct in the present setting:

Example 2 *Fix $r = 0.02, \lambda = 1, \beta = 4, A = 0$, and assume that the outside option is distributed according to the CDF*

$$F(u_o) = 0.05(ru_o) + 0.95(ru_o)^7.$$

Numerically maximizing $\pi(\phi)$ for the baseline technology $\theta_0 = 0.4, \mu = 15$, faster search $\theta_0 = 0.4, \mu = 20$, and better screening $\theta_0 = 0.35, \mu = 15$ yields:

Case	ϕ^*	Entry mass D^*	Utility $W_s^* - \phi^*$	Profit π^*
Baseline $(\mu, \theta_0) = (15, 0.4)$	1.0458	0.0935	33.6851	0.4796
Faster search $(\mu, \theta_0) = (20, 0.4)$	1.0346	0.0950	33.7920	0.4850
Better screening $(\mu, \theta_0) = (15, 0.35)$	1.0380	0.1153	35.1236	0.5632

Table 1: Better technology reduces the optimal fee.

Following either technological improvement, the optimal fee falls while profits rise. Thus, the platform does not necessarily capture the value of better technology by charging users more. Instead, it may profit from a lower fee because reducing the fee has a greater impact on search volume following the technological improvement. Note that this occurs even though the platform does not generate advertising revenue.

To understand the mechanism behind this phenomenon, note that at an interior optimum, the platform balances the marginal revenue from a higher fee against the induced loss in search volume. A technological improvement lowers the optimal fee when it makes search volume sufficiently more fee-elastic: at the old fee, raising the fee has become more costly in terms of lost volume, so the platform optimally cuts the fee. In such cases, better technology benefits users directly by improving the matching process and indirectly by inducing a lower fee, while still increasing the platform's profits.

The Relation Between Screening and Meeting Technologies

The baseline analysis treats the platform’s screening level and meeting rate as independently adjustable technologies. In many standard matching frameworks, these two dimensions are mechanically linked: implementing stricter screening reduces the pool of eligible partners, which would naturally decrease the meeting rate. By abstracting from this mechanical trade-off, we avoid having to specify the functional relationship between screening and meeting rates and can cleanly isolate how each dimension affects platform profitability.

Furthermore, if a platform does face such a mechanical trade-off, the marginal change in profits due to any marginal change in technology is straightforward to evaluate. By the envelope theorem, the marginal change in optimized profit equals the marginal change in search volume multiplied by revenue per round, plus the existing search volume multiplied by the marginal change in advertising revenue per round. Thus, the two marginal conditions derived above directly provide the building blocks to analyze any specific technological trade-off.

Competition

The model also provides a simple way to discuss competitive pressure. In the baseline analysis, agents differ in their outside option u_o . This outside option can be interpreted broadly as including the value of using rival platforms. Under this interpretation, competitors’ fees and matching technologies are summarized by the distribution F . A rival platform’s lower fee or improved matching technology changes the outside-option environment faced by the focal platform.

This representation yields a clear implication for pricing. The platform’s first-order condition (8) can be written as

$$\frac{f(u_o^*)}{F(u_o^*)} = \frac{r}{\beta\alpha'_s(\phi^*)} \left(\frac{1}{\phi^* + A/\mu} - \frac{\alpha'_s(\phi^*)}{\alpha_s(\phi^*)} \right).$$

The right-hand side is pinned down by the focal platform’s technology and revenue model, while the outside-option distribution enters only through the reverse hazard rate evaluated at the marginal entrant. Thus, competitive pressure affects the platform’s optimal fee through its effect on this local demand object. If the platform has a unique, strictly positive optimal fee, then a change in competitors’ offerings that raises the reverse hazard

rate at the pre-change marginal entrant induces the focal platform to lower its fee; a change that lowers the reverse hazard rate induces the platform to raise its fee.

Implications for Labor-Market Platforms

As in the marriage market, new search technologies have changed the way people search for a job, and online platforms are playing an increasingly important role in matching employers and workers. The main modeling difference between marriage and labor markets is the transferability of utility: marriage market models typically assume that utility is nontransferable, whereas labor market models typically assume that utility is transferable.

Online Appendix B shows that this difference does not by itself change the analysis. If a match with fit α after τ units of time generates total flow surplus $2u(\alpha, \tau)$, and this surplus is split according to the Nash bargaining solution with equal bargaining weights, then each side's continuation payoff coincides with the payoff in the nontransferable-utility model. As a result, the baseline model's equilibrium search, separation, and return behavior can also be sustained under transferable utility.

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A Proofs

Proof of Lemma 2. By Lemma 1, separation behavior is characterized by a cutoff $\alpha_s \in [0, \theta_0]$. The value of joining the platform is bounded from above by $\frac{\mu}{\mu+r} \frac{1}{r}$: the first ratio is the expected discount factor at the time of the next meeting, and the second ratio is an upper bound on the discounted payoff from a match. On the other hand, the discounted payoff from staying in a match with fit α is $\frac{1-\beta\alpha}{r}$. Thus, it is suboptimal to terminate a match of fit $\alpha \in [0, \frac{1-\mu/(\mu+r)}{\beta})$. In a nontrivial equilibrium we have that $F(W_s - \phi) > 0$, and since $F(u_o) = 0$ for $u_o \leq 0$ this implies $W_s - \phi > 0$. By (2), $W_s - \phi = (1 - \beta\alpha_s)/r$, and so $\alpha_s < 1/\beta$.

Thus, the cutoff in a nontrivial equilibrium is interior. Equation (2) follows from a simple algebraic manipulation of the indifference condition in the main text. ■

Proof of Proposition 1. First, we consider nontrivial equilibria in which agents choose to separate from a partner and return to the platform with positive probability. To analyze such an equilibrium we assume that $\alpha_s < 1/\beta$, and at the end of this part of the proof we verify that this inequality holds under Condition (4).

Characterization. We begin by expressing σ , W_s , EV_s , and EV_n as functions of α_s and the primitives of the model. This will later enable us to use Equation (3) to characterize the optimal α_s .

First, we calculate the expected value of a successful match. Fix $\alpha \in [0, \alpha_s]$. The flow payoff to a couple with fit α increases while $\theta_\tau > \alpha$ and is constant thereafter. Integrating (1) yields

$$\theta_\tau = e^{-\lambda\tau} \theta_0,$$

and so the payoff is increasing for $\tau < T(\alpha)$, where

$$T(\alpha) \equiv \frac{1}{\lambda} \log \left(\frac{\theta_0}{\alpha} \right). \quad (\text{A.1})$$

It follows that the discounted payoff from an indefinite match between such a couple is

$$V_s(\alpha) = \int_0^{T(\alpha)} e^{-r\tau} (1 - e^{-\lambda\tau} \beta \theta_0) d\tau + e^{-rT(\alpha)} \frac{1 - \beta\alpha}{r} = \frac{\lambda - \alpha\beta\lambda \left(\frac{\theta_0}{\alpha} \right)^{-\frac{r}{\lambda}} - \theta_0\beta r + r}{r(\lambda + r)}.$$

Since the fit of a successful match is distributed uniformly on $[0, \alpha_s]$, the expected payoff

from such a match is given by

$$EV_s = \int_0^{\alpha_s} \frac{V_s(\alpha)}{\alpha_s} d\alpha = \frac{\lambda - \frac{\alpha_s \beta \lambda^2 \left(\frac{\theta_0}{\alpha_s}\right)^{-\frac{r}{\lambda}}}{2\lambda+r} - \theta_0 \beta r + r}{r(\lambda + r)}. \quad (\text{A.2})$$

Next, we calculate the expected payoff (minus the cost of rejoining the platform) that an agent receives from an unsuccessful match. Note that, by definition, this payoff does not include the future payoff from rejoining the platform. Fix $\alpha \in (\alpha_s, \theta_0)$. A match of fit α lasts until θ_t drops to α ; that is, it lasts for $T(\alpha)$ units of time. It follows that the discounted payoff from such a match is

$$V_n(\alpha) = \int_0^{T(\alpha)} e^{-r\tau} (1 - e^{-\lambda\tau} \beta \theta_0) d\tau - e^{-rT(\alpha)} \phi = \frac{(\lambda - \theta_0 \beta r + r) - \left(\frac{\theta_0}{\alpha}\right)^{-\frac{r}{\lambda}} (\lambda + r(1 - \alpha\beta + \phi(\lambda + r)))}{r(\lambda + r)}.$$

The distribution of α in unsuccessful matches is uniform over $(\alpha_s, \theta_0]$. Taking the expectation over the above payoff yields

$$EV_n = \int_{\alpha_s}^{\theta_0} \frac{V_n(\alpha)}{\theta_0 - \alpha_s} d\alpha = \frac{\theta_0 r \left(1 - \lambda\phi - \frac{\theta_0 \beta (\lambda+r)}{2\lambda+r}\right) - \alpha_s \left(\lambda + r - \theta_0 \beta r + \lambda \left(\frac{\theta_0}{\alpha_s}\right)^{-\frac{r}{\lambda}} \left(\frac{\alpha_s \beta r}{2\lambda+r} - r\phi - 1\right)\right)}{r(\theta_0 - \alpha_s)(\lambda + r)}. \quad (\text{A.3})$$

The expected discount factor at the end of an unsuccessful match is

$$\sigma = \mathbb{E} \left(e^{-rT(\alpha)} \mid \alpha \sim U[\alpha_s, \theta_0] \right) = \frac{\lambda \left(\theta_0 - \alpha_s \left(\frac{\alpha_s}{\theta_0} \right)^{r/\lambda} \right)}{(\theta_0 - \alpha_s)(\lambda + r)}. \quad (\text{A.4})$$

Finally, since agents' tastes are distributed uniformly around the circle, we have that

$$\gamma = \frac{\alpha_s}{\theta_0}, \quad (\text{A.5})$$

and by (2) we have that

$$W_s = \frac{1 - \alpha_s \beta}{r} + \phi. \quad (\text{A.6})$$

Plugging (A.2)–(A.6) into Equation (3) and rearranging yields Equation (5).

Existence and Uniqueness. To see that the nontrivial equilibrium, if it exists, is unique, note that the LHS of Equation (5) is continuous and strictly increasing in α_s , whereas its RHS is constant in α_s .

To show that a nontrivial equilibrium exists we must show that there exists $\alpha_s \in (0, 1/\beta)$ that solves Equation (5). The RHS of Equation (5) is strictly positive and independent of α_s . On the other hand, the LHS of Equation (5) is increasing in α_s and equals zero if evaluated at $\alpha_s = 0$. Therefore, a nontrivial equilibrium exists if the LHS evaluated at the boundary $\alpha_s = 1/\beta$ exceeds the RHS; that is, if

$$\frac{1 - \xi(\beta\theta_0)^{\xi+1}(\beta\theta_0(\xi+1) - (\xi+2))}{\theta_0^{\xi+1}\beta^{1+\xi}(\xi+1)(\xi+2)} > \frac{r\phi(\mu+r)}{\mu}, \quad (\text{A.7})$$

a condition that is equivalent to (4). Moreover, under the assumption that agents act as if they were pivotal, it must be the case that if the above condition holds, then the agents' unique optimal strategy is given by the interior solution of (5). That is, if (A.7) is satisfied, agents whose outside option is less than $\frac{1-\beta\alpha_s}{r} > 0$ find it optimal to join the platform. Hence, for such values of α_s , there is no trivial equilibrium. The critical value of the outside option follows immediately from Equation (2).

Finally, consider the trivial equilibrium. In the trivial equilibrium agents join the platform with probability zero. The previous analysis shows that if (4) does not hold, then an agent's expected payoff from joining the platform is non-positive. Since an agent's outside option is strictly positive with probability one, if (4) does not hold, there is only a trivial equilibrium in which agents do not join the platform. Note that in this case the separation threshold is irrelevant, and so there are multiple equilibria that support the same trivial outcome. ■

Proof of Lemma 3. We derive this result by conducting comparative statics on Equation (5).

First consider changes in ϕ . Note that the LHS of (5) is increasing in α_s^* and independent of ϕ , whereas the RHS of (5) is increasing in ϕ and independent of α_s^* . It follows that α_s^* is increasing in ϕ .

Now, consider changes in θ_0 . Multiplying Equation (5) by θ_0 yields

$$(\xi^2 + 2\xi)(\lambda\xi + \lambda + \mu)\alpha_s^* + \frac{\mu}{\theta_0^{\xi+1}}(\alpha_s^*)^{\xi+2} = \theta_0\mu\xi(\xi+1) + \frac{\xi(\xi+2)(\lambda(\xi+1)(\lambda\xi\phi + \mu\phi + 1))}{\beta}.$$

Note that the LHS of this expression is decreasing in θ_0 , whereas the RHS is increasing in θ_0 . Since the LHS is increasing in α_s^* and the RHS is independent of α_s^* , it follows that an increase in θ_0 leads to an increase in α_s^* .

Next, consider changes in μ . Rearranging Equation (5) yields

$$\mu \left(\left(\frac{\alpha_s^*}{\theta_0} \right)^{\xi+2} + \frac{\alpha_s^*\xi(\xi+2)}{\theta_0} - \frac{\lambda\xi(\xi+1)(\xi+2)\phi}{\beta\theta_0} - \xi(\xi+1) \right) = \frac{\lambda\xi(\xi+1)(\xi+2)(1 - \alpha_s^*\beta + \lambda\xi\phi)}{\beta\theta_0}.$$

The LHS of this equation is increasing in α_s^* whereas the RHS is decreasing in α_s^* . Moreover, since $\alpha_s^* < 1/\beta$ the RHS of this equation is positive, and so the multiplier of μ in the LHS must be positive as well. Hence, an increase in μ leads to a decrease in α_s^* .

Since the conversion rate is defined by $\gamma = \alpha_s^*/\theta_0$, it follows immediately that the conversion rate is decreasing in μ and increasing in ϕ . To show that better screening increases the conversion rate, substitute $\alpha_s^* = \gamma\theta_0$ in Equation (5) and obtain the following implicit characterization of the conversion rate:

$$\mu\gamma^{\xi+2} + \gamma\xi(\xi+2)(\lambda\xi + \lambda + \mu) = \frac{\xi(\xi+2)(\lambda(\xi+1)(\lambda\xi\phi + \mu\phi + 1))}{\theta_0\beta} + \mu\xi(\xi+1). \quad (\text{A.8})$$

Note that the RHS of (A.8) is decreasing in θ_0 and independent of γ , whereas the LHS of (A.8) is increasing in γ and independent of θ_0 . It follows that γ is decreasing in θ_0 . ■

Proof of Proposition 2. By the implicit function theorem, $\alpha_s(\phi)$ (which is given by the unique solution of (5)) is differentiable. Consider the relaxed maximization problem where the platform chooses a fee in $[0, \bar{\phi}]$. In the relaxed problem, the platform maximizes a continuous profit function over a closed interval, and hence an optimal fee exists. Furthermore, the platform's profit from setting $\bar{\phi}$ is zero, whereas for sufficiently small ϕ demand is positive, and hence profits are positive. Thus, the solution of the relaxed problem is admissible in the profit maximization problem, and so a solution exists to that problem.

The derivative of the firm's profit with respect to ϕ is

$$\pi'(\phi) = V'(\phi)(\phi + A/\mu) + V(\phi) \quad (\text{A.9})$$

Note that

$$V'(\phi) = \frac{D'(\phi)}{\gamma(\phi)} - \gamma'(\phi) \frac{D(\phi)}{(\gamma(\phi))^2} = \frac{D'(\phi)}{\gamma(\phi)} - \frac{\alpha'_s(\phi)}{\alpha_s(\phi)} V(\phi).$$

In an interior optimum, this derivative must equal zero. Hence, in an interior optimum

$$\left(\frac{D'(\phi)}{\gamma(\phi)} - \frac{\alpha'_s(\phi)}{\alpha_s(\phi)} V(\phi) \right) (\phi + A/\mu) + V(\phi) = 0.$$

Next, we show that there is a unique optimal fee under condition (9). To do so, we show that the profit function is strictly log-concave. By Equation (2) the expected utility from joining the platform is $W_j(\phi) \equiv W_s(\phi) - \phi = \frac{1 - \beta\alpha_s(\phi)}{r}$. It follows that

$$\alpha_s(\phi) = (1 - rW_j(\phi))/\beta,$$

and so the platform's profit is

$$\pi(\phi) = \theta_0 \beta (\phi + A/\mu) \frac{F(W_j(\phi))}{1 - rW_j(\phi)}.$$

Thus,

$$\log\{\pi(\phi)\} = \log\{\theta_0 \beta\} + \log\{\phi + A/\mu\} + g(W_j(\phi)),$$

where $g(W_j(\phi)) = \log\{\frac{F(W_j(\phi))}{1 - rW_j(\phi)}\}$. Since $\log$ is a strictly concave function, to show that $\pi(\phi)$ is log-concave, it is enough to show that $g(W_j(\phi))$ is concave in ϕ . That is, to show that

$$\frac{d^2}{d\phi^2} g(W_j(\phi)) = g''(W_j(\phi)) W_j'(\phi)^2 + g'(W_j(\phi)) W_j''(\phi) \leq 0.$$

Since $g(\cdot)$ is strictly increasing, a sufficient condition for concavity of $g(W_j(\phi))$ is

$$-\frac{g''(W_j(\phi))}{g'(W_j(\phi))} \geq \frac{W_j''(\phi)}{W_j'(\phi)^2} \quad \forall \phi \in (0, \bar{\phi}).$$

Since $W_j(\phi) = \frac{1-\beta\alpha_s(\phi)}{r}$, we have that

$$\frac{W_j''(\phi)}{W_j'(\phi)^2} = \frac{r}{\beta} \left(-\frac{\alpha_s''(\phi)}{\alpha_s'(\phi)^2} \right).$$

Implicit differentiation of Equation (5) yields

$$\alpha_s'(\phi) = \frac{\theta_0^{1+\xi} \lambda \xi (\xi + 1) (\lambda \xi + \mu)}{\alpha_s^{1+\xi} \beta \mu + \theta_0^{1+\xi} \beta \xi (\lambda \xi + \lambda + \mu)}. \quad (\text{A.10})$$

This, in turn, implies that

$$-\frac{\alpha_s''(\phi)}{\alpha_s'(\phi)^2} = \frac{\mu(\xi + 1)\alpha_s(\phi)^\xi}{\mu \alpha_s(\phi)^{\xi+1} + \theta_0^{\xi+1} \xi (\lambda \xi + \lambda + \mu)}.$$

In a nontrivial continuation equilibrium $\alpha_s(\phi) \in (0, 1/\beta)$ (see Lemma 2), hence

$$\frac{W_j''(\phi)}{W_j'(\phi)^2} \leq \frac{r}{\beta} \sup_{\alpha \in (0, 1/\beta)} \frac{\mu(\xi + 1)\alpha^\xi}{\mu \alpha^{\xi+1} + \theta_0^{\xi+1} \xi (\lambda \xi + \lambda + \mu)} \equiv \underline{k}.$$

Therefore, if for all $W_j \in (0, W_s(0))$,

$$-\frac{d^2}{dW_j^2} \log \left(\frac{F(W_j)}{1 - rW_j} \right) \geq \underline{k} \frac{d}{dW_j} \log \left(\frac{F(W_j)}{1 - rW_j} \right),$$

then $g(W_j(\phi))$ is concave on $(0, \bar{\phi})$, and $\log \pi(\phi)$ is strictly concave on $(0, \bar{\phi})$. Hence $\pi(\phi)$ is strictly log-concave and admits a unique maximizer. ■

Proof of Proposition 3. By Lemma 3, a higher fee raises $\alpha_s(\phi)$. Hence, differentiating $V(\phi) = D(\phi)/\gamma(\phi)$ gives

$$V_\phi(\phi) = \theta_0 \left[\frac{f \left(\frac{1-\beta\alpha_s(\phi)}{r} \right)}{\alpha_s(\phi)} \left(-\frac{\beta\alpha_s'(\phi)}{r} \right) - \frac{F \left(\frac{1-\beta\alpha_s(\phi)}{r} \right) \alpha_s'(\phi)}{\alpha_s(\phi)^2} \right] < 0.$$

Take $A_2 > A_1$ and any $\phi_i \in \Phi^*(A_i)$, $i = 1, 2$. Optimality gives

$$V(\phi_2) \left(\phi_2 + \frac{A_2}{\mu} \right) \geq V(\phi_1) \left(\phi_1 + \frac{A_2}{\mu} \right)$$

and

$$V(\phi_1) \left(\phi_1 + \frac{A_1}{\mu} \right) \geq V(\phi_2) \left(\phi_2 + \frac{A_1}{\mu} \right).$$

Adding these inequalities yields

$$\frac{A_2 - A_1}{\mu} (V(\phi_2) - V(\phi_1)) \geq 0.$$

Since V is strictly decreasing, $\phi_2 \leq \phi_1$. Suppose now that $\phi_1 > 0$ and, toward a contradiction, that $\phi_2 = \phi_1 = \hat{\phi}$. The common optimum is interior, so the first-order condition holds at both advertising levels:

$$V(\hat{\phi}) + V_{\phi}(\hat{\phi}) \left(\hat{\phi} + \frac{A_i}{\mu} \right) = 0, \quad i = 1, 2.$$

Subtracting the two conditions gives

$$V_{\phi}(\hat{\phi}) \frac{A_2 - A_1}{\mu} = 0,$$

which contradicts $V_{\phi}(\hat{\phi}) < 0$. Hence $\phi_2 < \phi_1$ whenever $\phi_1 > 0$.

Denote the profit as a function of fee and advertising revenue by

$$\pi_A(\phi) \equiv V(\phi) \left(\phi + \frac{A}{\mu} \right),$$

and for any $\phi \in (0, \bar{\phi})$, define

$$R(\phi) \equiv \frac{\mu \phi V(\phi)}{V(0) - V(\phi)}.$$

The denominator is strictly positive because V is strictly decreasing. The profit difference between a zero fee and a positive fee is

$$\begin{aligned} \pi_A(0) - \pi_A(\phi) &= \frac{A}{\mu} V(0) - V(\phi) \left(\phi + \frac{A}{\mu} \right) \\ &= \frac{V(0) - V(\phi)}{\mu} (A - R(\phi)). \end{aligned}$$

It remains to show that the supremum of R is finite. The function R is continuous on

$(0, \bar{\phi})$. Since V is differentiable at zero and $V_\phi(0) < 0$,

$$\lim_{\phi \downarrow 0} R(\phi) = -\mu \frac{V(0)}{V_\phi(0)} \in (0, \infty).$$

By continuity of Equation (5) and the definition of $\bar{\phi}$ in Equation (4),

$$\alpha_s(\phi) \longrightarrow \frac{1}{\beta} \quad \text{as} \quad \phi \uparrow \bar{\phi}.$$

Consequently,

$$D(\phi) = F\left(\frac{1 - \beta\alpha_s(\phi)}{r}\right) \longrightarrow F(0) = 0,$$

whereas

$$\gamma(\phi) = \frac{\alpha_s(\phi)}{\theta_0} \longrightarrow \frac{1}{\beta\theta_0} > 0.$$

It follows that $V(\phi) = D(\phi)/\gamma(\phi) \rightarrow 0$, and therefore

$$\lim_{\phi \uparrow \bar{\phi}} R(\phi) = 0.$$

Thus R has a continuous extension to the compact interval $[0, \bar{\phi}]$, and consequently $A^\dagger(\theta_0, \mu) \equiv \sup_{\phi \in (0, \bar{\phi})} \frac{\mu\phi V(\phi)}{V(0) - V(\phi)}$ is an element of $(0, \infty)$.

To conclude the proof, note the following three observations. If $A < A^\dagger$, then, by the definition of the supremum, there exists a positive fee ϕ such that $R(\phi) > A$. Hence zero is not optimal. If $A = A^\dagger$, then $A \geq R(\phi)$ for every positive fee, and hence zero is optimal. Finally, if $A > A^\dagger$, then $A > R(\phi)$ for every positive fee, and hence zero is the unique optimum. ■

Proof of Proposition 4. The platform's optimal profit is

$$\pi^*(\theta_0, \mu, A) = V(\phi^*(\theta_0, \mu, A); \theta_0, \mu) \left(\phi^*(\theta_0, \mu, A) + \frac{A}{\mu} \right).$$

The upper boundary is not binding: at $\phi = \bar{\phi}(\theta_0, \mu)$ demand is zero and profit is zero, whereas the maximized profit is strictly positive. Thus, the dependence of the upper boundary on θ_0 and μ does not contribute to the marginal change in optimized profit. Since Condition (9) gives a unique optimal fee, the envelope theorem (Milgrom and Segal,

2002, Theorem 1) implies that

$$\frac{\partial \pi^*(\theta_0, \mu, A)}{\partial \theta_0} = \frac{\partial}{\partial \theta_0} \left[V(\phi; \theta_0, \mu) \left(\phi + \frac{A}{\mu} \right) \right] \Big|_{\phi=\phi^*(\theta_0, \mu, A)}.$$

Since θ_0 enters the objective only through V , and V is differentiable with respect to θ_0 , this becomes

$$\frac{\partial \pi^*(\theta_0, \mu, A)}{\partial \theta_0} = \left(\phi^*(\theta_0, \mu, A) + \frac{A}{\mu} \right) \frac{\partial V(\phi; \theta_0, \mu)}{\partial \theta_0} \Big|_{\phi=\phi^*(\theta_0, \mu, A)}.$$

Since the platform's optimal profit is strictly positive, the term multiplying the derivative of V is strictly positive. It follows that

$$\frac{\partial \pi^*(\theta_0, \mu, A)}{\partial \theta_0} > 0 \iff \frac{\partial V(\phi; \theta_0, \mu)}{\partial \theta_0} \Big|_{\phi=\phi^*(\theta_0, \mu, A)} > 0.$$

Recall that better screening is a decrease in θ_0 . Therefore, a marginal improvement in screening reduces optimized profits if and only if volume is increasing in θ_0 at the optimal fee, which is exactly condition (10).

Since V is differentiable with respect to μ , by the same envelope theorem

$$\begin{aligned} \frac{\partial \pi^*(\theta_0, \mu, A)}{\partial \mu} &= \frac{\partial}{\partial \mu} \left[V(\phi; \theta_0, \mu) \left(\phi + \frac{A}{\mu} \right) \right] \Big|_{\phi=\phi^*(\theta_0, \mu, A)} = \\ &= \frac{\partial V(\phi; \theta_0, \mu)}{\partial \mu} \Big|_{\phi=\phi^*(\theta_0, \mu, A)} \left(\phi^*(\theta_0, \mu, A) + \frac{A}{\mu} \right) - \frac{AV(\phi^*(\theta_0, \mu, A); \theta_0, \mu)}{\mu^2}. \end{aligned}$$

Therefore, a marginal increase in the speed of search reduces profits if and only if

$$\frac{\partial V(\phi; \theta_0, \mu)}{\partial \mu} \Big|_{\phi=\phi^*(\theta_0, \mu, A)} \left(\phi^*(\theta_0, \mu, A) + \frac{A}{\mu} \right) < \frac{AV(\phi^*(\theta_0, \mu, A); \theta_0, \mu)}{\mu^2},$$

which is exactly condition (11). ■

Proof of Proposition 5. We first prove the result for $A = 0$.

Consider first an increase in search speed, holding screening fixed. When $A = 0$, profit from a fixed fee ϕ is

$$\phi V(\phi; \theta_0, \mu).$$

At every fixed fee in the nontrivial region, Lemma 3 implies that an increase in μ lowers

$\alpha_s(\phi; \theta_0, \mu)$. Moreover, by condition (4) $\bar{\phi}$ is increasing in μ and so the old fee remains feasible. Therefore, following an increase in μ , demand

$$D(\phi; \theta_0, \mu) = F \left(\frac{1 - \beta \alpha_s(\phi; \theta_0, \mu)}{r} \right)$$

increases, while the conversion rate

$$\gamma(\phi; \theta_0, \mu) = \frac{\alpha_s(\phi; \theta_0, \mu)}{\theta_0}$$

decreases. Hence

$$V(\phi; \theta_0, \mu) = \frac{D(\phi; \theta_0, \mu)}{\gamma(\phi; \theta_0, \mu)}$$

strictly increases at every fixed positive fee. If $A = 0$, then every optimal fee is strictly positive, and so after an increase in μ , the platform's profit increases even if it does not adjust its fee. Reoptimization can only increase profit further.

Now consider an improvement in screening, holding μ fixed. It is useful to reparameterize the platform's choice by the separation threshold α that the fee implements. Solving (5) for the fee that implements $\alpha \in (0, 1/\beta)$ gives

$$\phi(\alpha; \theta_0, \mu) = \frac{1}{\lambda\xi + \mu} \left\{ \frac{\beta(\lambda\xi + \lambda + \mu)}{\lambda(\xi + 1)}\alpha + \frac{\beta\mu}{\lambda\xi(\xi + 1)(\xi + 2)} \frac{\alpha^{\xi+2}}{\theta_0^{\xi+1}} - \frac{\beta\mu}{\lambda(\xi + 2)}\theta_0 - 1 \right\}. \quad (\text{A.11})$$

When $A = 0$, the profit from implementing α is

$$F \left(\frac{1 - \beta\alpha}{r} \right) \frac{\theta_0 \phi(\alpha; \theta_0, \mu)}{\alpha}.$$

For fixed α , the demand term does not depend on θ_0 . Thus, the sign of the marginal effect of increasing θ_0 at a fixed implementable separation threshold is the sign of

$$\frac{\partial}{\partial \theta_0} \left(\frac{\theta_0 \phi(\alpha; \theta_0, \mu)}{\alpha} \right).$$

Using (A.11),

$$\frac{\partial}{\partial \theta_0} \left(\frac{\theta_0 \phi(\alpha; \theta_0, \mu)}{\alpha} \right) = \frac{1}{\alpha(\lambda\xi + \mu)} \left\{ \frac{\beta}{\lambda(\xi + 1)} \left[(\lambda\xi + \lambda + \mu)\alpha - \frac{\mu}{\xi + 2} \frac{\alpha^{\xi+2}}{\theta_0^{\xi+1}} - \frac{2\mu(\xi + 1)}{\xi + 2} \theta_0 \right] - 1 \right\}.$$

Since $\alpha \in (0, 1/\beta)$, we have

$$(\lambda\xi + \lambda + \mu)\alpha \leq \frac{\lambda\xi + \lambda + \mu}{\beta},$$

and the term

$$-\frac{\mu}{\xi + 2} \frac{\alpha^{\xi+2}}{\theta_0^{\xi+1}}$$

is nonpositive. Hence the expression in braces is bounded above by

$$\frac{\mu}{\lambda} \left(\frac{1}{\xi + 1} - \frac{2\beta\theta_0}{\xi + 2} \right).$$

Because $\xi > 0$ implies

$$\frac{2}{\xi + 2} > \frac{1}{\xi + 1},$$

and Assumption 1 implies $\beta\theta_0 > 1$, this upper bound is strictly negative. Therefore

$$\frac{\partial}{\partial\theta_0} \left(\frac{\theta_0\phi(\alpha; \theta_0, \mu)}{\alpha} \right) < 0.$$

Thus, lowering θ_0 strictly raises profit at every fixed implementable separation threshold α . Because the improved technology satisfies Assumption 1, the same $\alpha \in (0, 1/\beta)$ remains below the maximal feasible separation threshold. Moreover, differentiating (A.11) gives

$$\frac{\partial\phi(\alpha; \theta_0, \mu)}{\partial\theta_0} < 0.$$

Hence, lowering θ_0 raises the fee required to implement the same α . Since the old $A = 0$ optimal fee is strictly positive, the same separation threshold is implementable after the screening improvement with a nonnegative fee. Thus, after an improvement in screening, the platform can implement the same separation threshold as before and earn strictly higher profit. Reoptimization can only increase profit further.

Combining the two comparisons sequentially, first from $\langle \theta_0, \mu \rangle$ to $\langle \theta_0, \mu' \rangle$ and then from $\langle \theta_0, \mu' \rangle$ to $\langle \theta'_0, \mu' \rangle$, shows that the improved technology yields weakly higher profit at $A = 0$ at each step and strictly higher profit in at least one step.

By continuity of the optimized-profit function in A , the strict ranking at $A = 0$ persists

for all sufficiently small A . That is, there exists $\underline{A} > 0$ such that

$$\pi^*(\theta'_0, \mu', A) > \pi^*(\theta_0, \mu, A)$$

for every $A \in [0, \underline{A}]$. ■

Proof of Proposition 6. By (6), Assumption 2 holds for both technologies for all sufficiently small r . We restrict attention to such r .

Fix a technology $\langle \theta_0, \mu \rangle$. The assumption of large advertising revenue is used only at the end of the proof, where it ensures that the optimal fee is zero. We first characterize zero-fee advertising exposure in the patient-agent limit.

Let $\gamma_r^0(\theta_0, \mu)$ denote the conversion rate induced by the zero fee when the discount rate is r . At $\phi = 0$, the conversion-rate characterization (A.8) becomes

$$\mu (\gamma_r^0)^{\xi+2} + \gamma_r^0 \xi(\xi+2)(\lambda\xi + \lambda + \mu) = \frac{\xi(\xi+2)\lambda(\xi+1)}{\theta_0\beta} + \mu\xi(\xi+1), \quad (\text{A.12})$$

where $\xi = r/\lambda$ and where we suppress the arguments (θ_0, μ) of γ_r^0 .

As $r \rightarrow 0$, the right-hand side of (A.12) converges to 0. It follows that $\gamma_r^0 \rightarrow 0$ as well.

Now consider zero-fee advertising profit. At a zero fee, demand is

$$G(1 - \beta\theta_0\gamma_r^0(\theta_0, \mu)),$$

and the expected number of search rounds per potential entrant is demand times $1/\gamma_r^0$. Hence zero-fee advertising exposure as a function of technology and discounting is

$$Z_r(\theta_0, \mu) \equiv \frac{V_r(0; \theta_0, \mu)}{\mu} = \frac{G(1 - \beta\theta_0\gamma_r^0(\theta_0, \mu))}{\mu\gamma_r^0(\theta_0, \mu)}.$$

The preceding limit implies that $Z_r(\theta_0, \mu)$ diverges as $r \rightarrow 0$. Therefore, to compare technologies in the patient limit, we normalize exposure by multiplying it by $\sqrt{r}$. Since

$$\lim_{r \rightarrow 0} G(1 - \beta\theta_0\gamma_r^0(\theta_0, \mu)) = 1,$$

we have

$$\lim_{r \rightarrow 0} \sqrt{r} Z_r(\theta_0, \mu) = \lim_{r \rightarrow 0} \frac{\sqrt{r}}{\mu\gamma_r^0(\theta_0, \mu)}$$

We now show that this limit equals

$$H(\theta_0, \mu) = \sqrt{\frac{\lambda}{\mu \left(\mu + \frac{2\lambda}{\beta\theta_0} \right)}}.$$

The first step is to show that $(\gamma_r^0)^\xi \rightarrow 1$ as $r \rightarrow 0$. Rewrite (A.12) as

$$\mu (\gamma_r^0)^{\xi+2} + \xi(\xi+2)(\lambda\xi + \lambda + \mu)\gamma_r^0 = \xi \left[\frac{(\xi+2)\lambda(\xi+1)}{\theta_0\beta} + \mu(\xi+1) \right].$$

Since $0 < \gamma_r^0 < 1$, we have

$$(\gamma_r^0)^{\xi+2} \leq \gamma_r^0.$$

Thus,

$$[\mu + \xi(\xi+2)(\lambda\xi + \lambda + \mu)] \gamma_r^0 / \xi \geq \left[\frac{(\xi+2)\lambda(\xi+1)}{\theta_0\beta} + \mu(\xi+1) \right].$$

Dividing by μ and taking the limit inferior as $\xi \rightarrow 0$ gives

$$\liminf_{\xi \rightarrow 0} \gamma_r^0 / \xi \geq 1 + \frac{2\lambda}{\mu\theta_0\beta}.$$

Therefore, there exists $c > 0$ such that for all sufficiently small ξ ,

$$\gamma_r^0 \geq c\xi.$$

Since also $\gamma_r^0 < 1$,

$$\log(c\xi) \leq \log \gamma_r^0 \leq 0.$$

Multiplying by ξ and using $\xi \log(c\xi) \rightarrow 0$ gives

$$\xi \log \gamma_r^0 \rightarrow 0.$$

Thus,

$$(\gamma_r^0)^\xi = e^{\xi \log \gamma_r^0} \rightarrow 1.$$

We now use this limit to derive the limit exposure. Dividing (A.12) by ξ gives

$$\mu (\gamma_r^0)^\xi \frac{(\gamma_r^0)^2}{\xi} + \gamma_r^0(\xi+2)(\lambda\xi + \lambda + \mu) = \frac{(\xi+2)\lambda(\xi+1)}{\theta_0\beta} + \mu(\xi+1).$$

Since $\gamma_r^0 \rightarrow 0$ and $(\gamma_r^0)^\xi \rightarrow 1$, we obtain

$$\lim_{r \rightarrow 0} \frac{(\gamma_r^0(\theta_0, \mu))^2}{r} = \frac{1}{\lambda} + \frac{2}{\beta\theta_0\mu}.$$

The limits derived above imply that

$$\lim_{r \rightarrow 0} \frac{\sqrt{r}}{\mu\gamma_r^0(\theta_0, \mu)} = \frac{1}{\mu\sqrt{\frac{1}{\lambda} + \frac{2}{\beta\theta_0\mu}}} = \sqrt{\frac{\lambda}{\mu\left(\mu + \frac{2\lambda}{\beta\theta_0}\right)}} = H(\theta_0, \mu).$$

The function H is increasing in θ_0 and decreasing in μ . Hence, because

$$\theta'_0 \leq \theta_0, \quad \mu' \geq \mu,$$

with at least one inequality strict,

$$H(\theta'_0, \mu') < H(\theta_0, \mu).$$

Because the two technologies are fixed and the limiting inequality is strict, the convergence of $\sqrt{r}Z_r$ to H implies the same strict ordering of Z_r for all sufficiently small r .

It remains to connect this zero-fee comparison to optimized profits. For each sufficiently small r , let $F_r(u) = G(ru)$, and let $A_r^\dagger(\theta_0, \mu)$ denote the threshold from Proposition 3 for discount rate r , outside-option distribution F_r , and technology $\langle \theta_0, \mu \rangle$. Define

$$\overline{A}(r) = 2 \max \{ A_r^\dagger(\theta_0, \mu), A_r^\dagger(\theta'_0, \mu') \}.$$

By Proposition 3, $\overline{A}(r) < \infty$ and, for every $A \geq \overline{A}(r)$, a zero fee is the unique optimal fee under both technologies. Therefore,

$$\Pi_r^*(\theta_0, \mu, A) = AZ_r(\theta_0, \mu), \quad \Pi_r^*(\theta'_0, \mu', A) = AZ_r(\theta'_0, \mu').$$

Since $A > 0$ and

$$Z_r(\theta'_0, \mu') < Z_r(\theta_0, \mu),$$

the improved technology lowers profit. ■

B Online Appendix: Transferable Utility

In the main text, we presented a model in which agents on both sides of the market cannot make any transfers. Such models are often used to analyze interactions in the marriage market. In this appendix, we allow couples to transfer utility, making the model suitable for analyzing interactions in the labor market. We then show that the equilibrium of the baseline model is also an equilibrium of the model with transferable utility.

Modify the model so that if agents x and y have been together for τ units of time, they generate a flow payoff of $2u(\alpha, \tau)$, where $u(\alpha, \tau)$ is as defined in the main text. We assume that agents x and y share the payoff according to the Nash bargaining solution with equal bargaining weights. This assumption is in line with various papers in the search-and-matching literature (see, e.g., [Shimer and Smith, 2000](#)). All other modeling assumptions remain as in the main text.

We shall refer to the model in the main text as the NTU model and to the model in the appendix as the TU model.

Proposition 7 *Any profile of strategies that constitutes an equilibrium in the NTU model is also an equilibrium in the TU model.*

Proof. Consider the TU model and a profile of strategies that is an equilibrium of the NTU model. Note that due to the symmetric bargaining weights, the symmetric strategies, and the symmetric distributions of singles on both sides of the market, each agent x obtains a flow payoff of $1 - \beta \cdot \max\{\alpha(x, y), \theta_\tau\}$ after spending τ units of time with agent y . Hence, the continuation value at any point in the game is the same as in the NTU model. Since no agent has a profitable deviation in the NTU model, it follows that no agent has a profitable deviation in the TU model, and so our profile constitutes an equilibrium in the TU model. ■