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

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Abstract

Should online matching platforms adopt new technologies that enable faster search and screening for better matches? We study this question through the lens of a platform-mediated two-sided search model. On the one hand, the platform wishes to provide high-quality search and matching services to attract repeat clientele, but on the other hand, it may wish to avoid inducing matches that are so good that agents never terminate them. We find that the platform benefits from reducing search frictions but suffers from improving the quality of matches, and show that both types of technology advances reduce the platform's optimal fee.

Keywords: Online Platforms, Search, Decentralized Matching, Learning.

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1 Introduction

The rise of online matching platforms has revolutionized matching markets by facilitating matching in a wide array of contexts ranging from dating and labor to commerce and tourism.[1] Compared to traditional forms of match-making, online matching platforms are better able to mitigate both search frictions by creating thick markets and information frictions by effectively utilizing big data to identify promising matches.

While online platforms have the ability to harness new technologies for the benefit of their users, it is important to remember that their primary objective remains profit maximization. This objective gives rise to a potential misalignment of interests: users join the platform to find a good match, but a good match may reduce their future usage, thereby decreasing the platform's profit. For example, the popular dating app Hinge claims that it uses its technology to provide such high-quality matches that it is "designed to be deleted." On the other hand, in February 2024 a federal lawsuit[2] filed against Match Group (which includes the popular dating apps Tinder and Hinge) claimed that Match's services "prioritize profits over customers' relationship goals" by "[h]arnessing powerful technologies and hidden algorithms" to "capture and sustain paying subscribers and keep them on-app."

At a glance, it may seem that a platform has an incentive to provide its users with "bad matches" in order to prevent them from leaving the platform permanently after finding a good match. However, providing bad matches reduces users' willingness to pay the platform for its services. In other words, the platform faces a tradeoff: providing a service that is "too good" can reduce its clientele base, whereas providing a service that is not good enough can reduce the fees it can charge from each user. This tradeoff affects the type of technologies that dating platforms adopt and the extent of their adoption.

In this paper, we develop a model of a platform-mediated matching market that allows us to explore the platform's incentives to adopt new matching technologies. We then explore how technology adoption shapes users' behavior and affects their overall welfare, taking the platform's (endogenous) pricing strategy into account. For concreteness, we present the model and the results through the lens of a specific application, namely, dating apps and the marriage market. In the concluding section we discuss why our analysis and

[1] For instance, since the turn of the 21st century, meeting online has gradually displaced the roles that family and friends once played in bringing couples together, becoming the most popular way couples meet (Rosenfeld, Thomas and Hausen, 2019).

[2] *Oksayan v. MatchGroup Inc.*, N.D. Cal., No. 3:24-cv-00888, 2/14/24.

insights apply in other contexts such as the labor market.[3]

In the model, there is a two-sided market that is controlled by a monopolistic profit-maximizing platform. Agents on both sides of the market join the platform in order to search for a partner. While they are on the platform, agents meet potential partners at random. A key aspect of the model is that when two agents meet, they do not know their exact *fit*. Their fit is revealed gradually as they spend time together off the platform. As agents gather more information about their fit, they can choose to stay with their partner or break up with them and return to the platform in order to find a more promising partner. This decision depends not only on their belief regarding their fit with the current partner, but also on their beliefs regarding (i) how long it will take them to find a new partner, (ii) how likely it is that they will find a new partner who is more suitable for them (i.e., a partner with whom they have a better fit), and (iii) how much it will cost to rejoin the platform.

The platform in our model is characterized by its technology, which consists of two components. The first component represents the platform's ability to screen relevant partners for its users. Agents in our model meet only potential partners with whom their fit is better than some threshold level θ_0. The second component represents the speed of search on the platform. While they are on the platform, agents meet relevant partners at a constant rate μ.[4]

In exchange for these services, the platform chooses a fee that agents have to pay in order to join the platform. The central tradeoff that the platform faces in setting its fee is as follows. On the one hand, a higher fee increases the payment collected from any user who chooses to return to the platform. On the other hand, a higher fee makes returning to the platform less attractive, which means that some users may decide to stay with their current partner rather than terminate their match and search for a more promising one. This, in turn, reduces the platform's repeat clientele base.

To investigate the platform's incentives to adopt new technologies, we first study the implications of improvements in the platform's technology on its profits, taking into account that it readjusts its pricing strategy. We show that a higher speed of search increases the platform's profits, whereas better screening reduces its profits. Roughly speaking, the difference between the effects of these two technological improvements arises due to their opposite effects on the size of the platform's repeat clientele base. An improvement in

[3]We conduct a formal analysis of this case in Online Appendix C.

[4]In Online Appendix B, we show that all of our results hold when the search technology is quadratic.

the speed of search makes returning to the platform more attractive for agents and, as a result, makes them break up with partners that they would stay with otherwise. Thus, such an improvement enlarges the repeat clientele base. An improvement in the level of screening also makes returning to the platform more attractive, but has an additional effect: it improves the quality of the matches proposed by the platform. We show that the latter effect dominates the former one, and so, overall, agents are less likely to break up with partners they meet on the platform. Thus, such an improvement shrinks the platform's repeat clientele base.

We then turn to consider the users' perspective. The platform's technology affects the optimal fee that it charges. We show that, under mild parametric assumptions, both types of technological advances (i.e., higher speed of search and/or better screening technology) reduce the platform's optimal fee. This prediction stands in contrast to the basic intuition that higher-quality products are associated with higher prices, and is intrinsically related to the repeat clientele tradeoff underlying the platform's profit maximization problem. This result suggests that the initial increase in consumer surplus due to technological advances is amplified by the platform's response in pricing.

Combining the above results, we can conclude that a higher speed of search leads to a Pareto improvement, but that there is a tension between the platform's profits and consumer surplus when it comes to better match screening: despite the positive effect on consumer welfare, better screening is not desirable from the platform's perspective. These results imply that when the platform is faced with the decision on how much to invest in each component of its technology, it has an incentive to invest in reducing search frictions and a disincentive to invest in improving its screening ability (these investment decisions are not modeled explicitly because, as the analysis shows, the platform's investment incentives can be understood without endogenizing the platform's investment decisions, which would require specifying the costs of such investments). This in turn suggests that users of online matching platforms should expect to meet a large number of potential partners, but not necessarily ones who are likely to be suitable for them. This prediction reflects the tension between profits and customer goals underlying the lawsuit against Match Group mentioned above.

We contribute to the matching-with-frictions literature in two dimensions. First, we propose a model with horizontal differentiation (and learning about match quality) that can be solved in closed form and that enables the derivation of comparative statics, which are typically difficult to obtain in such models (see Chade, Eeckhout and Smith, 2017, for a comprehensive review). Second, we introduce a matchmaking platform into the matching-with-frictions setting. While we are not the first to consider matchmaking in this context (as we discuss in the literature review, Bloch and Ryder, 2000, introduce a matchmaker into this setting as well), we are the first to study this matchmaker's incentives and the way they shape the matching market's outcomes. At the methodological level, we also contribute to the literature on platform design by introducing agents' search and learning incentives and considering a dynamic model that features repeat clientele.

The paper proceeds as follows. Section 2 presents the model. In Section 3, we characterize the equilibrium in closed form. In Section 4, we use this characterization to study the implications of technological advances on prices, profits, and welfare. In Section 5 we discuss the related literature, and in Section 6 we discuss extensions to the baseline model. Online Appendices B and C formally analyze two alternative specifications of the model.

2 The Model

We study an environment in which a monopolistic platform facilitates matching between two sets of agents. We assume that the two sets are symmetric.[5] The market operates in continuous time, and agents discount the future at a rate of $r > 0$. New agents enter the platform at a constant rate of $2\eta > 0$, with the inflow equally distributed between both sides of the market.

Agents are horizontally differentiated, that is, each agent has their own idiosyncratic preferences over potential partners. 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. We identify each agent by their (clockwise) distance from the top of the circle, and denote this characteristic by x. 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 arc between x and y. The platform then screens potential partners for its users by directing agents' search to

[5] In the concluding section, we explain why our model can also accommodate certain types of asymmetry between the two sides.

those potential partners with whom they have a (sufficiently) good fit, that is, for which $\alpha(x,y) \leq \theta_0$. We refer to θ_0 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 with whom they have a good fit at a constant rate of μ. Since the fit of a match is unobservable, all proposed matches are ex-ante symmetric. Hence, agents either reject all matches or leave the platform with their first proposed match (who also leaves the platform), Assumption (2) below rules out the former degenerate case.

Remark: In Online Appendix B, we analyze the model under an assumption that the search technology is quadratic (as in , e.g., Shimer and Smith, 2000; Smith, 2006). The key difference between the two search technologies is that under quadratic search the rate at which an agent meets potential partners is endogenous. Nevertheless, we show that all of our results remain valid under the alternative search technology.

Payoffs and learning. Utility in our model is nontransferable and the flow payoff to unmatched agents is normalized to zero.[6] We consider a setting where the flow payoff that agents receive while they are together is increasing in both their fit and the amount of time in which they have been together. Such payoff processes capture a natural idea: the better one knows their 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. However, the extent to which a relationship can be fine-tuned is bounded by the fit of the couple.

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 have been together for τ units of time is

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

where θ_t evolves according to

$$\frac{d\theta_t}{\theta_t} = -\lambda dt. \tag{1}$$

[6] We explain why our results continue to hold under transferable utility in Online Appendix C.

The parameter $\lambda > 0$ represents the rate at which a couple's payoff increases over time, while the parameter $\beta > 0$ measures the importance of fit. Throughout the paper we impose the qualitative assumption that agents prefer any (proposed) match to remaining unmatched;[7] that is, we assume that

$$\beta\theta_0 < 1. \tag{2}$$

The agents' flow payoffs are informative about their 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 became constant at $\sigma < \tau$, they will infer that $\alpha = \theta_\sigma$. 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 their fit is at least θ_0; after being together for 1 unit of time they infer that their fit is at least θ_1; and after spending 2 units of time together they learn their fit.

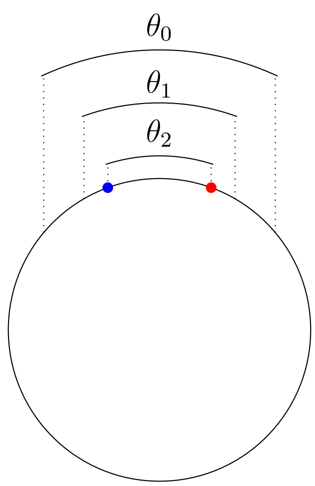

Figure 1: Learning technology.

Strategies. The platform's objective is to maximize its profit. Its strategy specifies a fee, $\phi \geq 0$, which agents pay every time they join the platform.[8,9] We impose a technical assumption that newly arriving agents do not need to pay the fee (i.e., "the first sample is free"). This assumption guarantees that the platform's optimal fee corresponds to the

[7]This assumption is standard in the matching-with-search-frictions literature. See, e.g., Burdett and Coles (1997), Shimer and Smith (2000), and Smith (2006).

[8]In reality, fees may be periodic rather than per match (e.g., a monthly fee). Such a pricing method is outcome equivalent to the one in our model (see Section 6 for an explanation).

[9]Monthly subscription fees can range from small amounts such as $7.99 to larger amounts such as $500 (e.g., Tinder Platinum).

solution of a first-order condition, and is commonly used in the consumer search literature in order to overcome the Diamond paradox (for a discussion, see, e.g., Burdett and Judd, 1983).

Each agent's strategy specifies two things: under what conditions to unilaterally terminate an existing match, and, after a match has been terminated, whether or not to pay the platform's fee and return to the platform. 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.

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 it is distributed uniformly on $[0, \theta_t]$.[10]

Threshold strategies. A couple's continuation payoff from a match (strictly) increases over time until their fit is revealed. By contrast, the value of joining 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 agents may find it optimal to terminate a match is when its fit is revealed. 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 strategies can be represented by a separation threshold $\alpha_s \in [0, \theta_0]$ such that*

[10] Focusing on such strategies is common in the matching-with-frictions literature; see Smith (2006) for a discussion.

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 on the arc of the "Successful" region leads to an indefinite relationship, whereas a match with a partner on the arc of the "Unsuccessful" regions leads to eventual separation and a return to the platform. There are no meetings with potential partners on the arc of the "Not Matched" region.

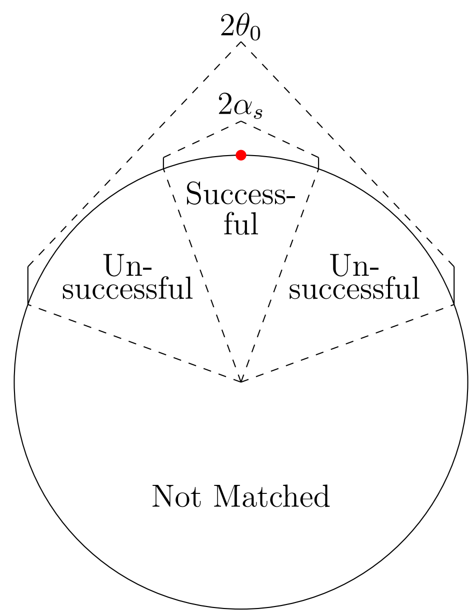

Figure 2: Strategies and outcomes.

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 the platform's technology and fee. That is, on $\langle \mu, \theta_0, \phi \rangle$. We say that the agents' strategy, α_s, constitutes a *continuation equilibrium* if it maximizes the agents' expected discounted payoff given $\langle \mu, \theta_0, \phi \rangle$.[11] We say that $\langle \phi, \alpha_s \rangle$ is an *equilibrium* if ϕ maximizes the platform's profit from each agent given α_s, and α_s is a continuation equilibrium.

[11] Assumption (2) implies that if agents optimally terminate a match, they will rejoin the platform. Hence, agents' optimal strategies can be described only by α_s.

3 Equilibrium

In this section, we characterize the equilibrium of the model. Since the model is sequential in nature, we start with the agents' behavior in the second stage, namely, their behavior given any fixed fee set by the platform. We show that there exists a unique continuation equilibrium and characterize it in closed form. We then turn to the platform's pricing problem in the first stage, and show that it also has a unique solution.

3.1 Agent's behavior on the platform

We start by analyzing the agents' behavior given a fixed fee. The (continuation) equilibrium can be either a *nontrivial equilibrium* in which agents terminate matches and rejoin the platform with positive probability, or a *trivial equilibrium* in which agents stay indefinitely with the first partner with whom they are matched.

The continuation value of an indefinite relationship for a couple $\langle x, y\rangle$ who have learned that their fit is $\alpha(x, y)$ 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 $W_s - \phi$. The equilibrium separation threshold α_s is the fit α for which the agents are indifferent whether to stay together or terminate their match and 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, strategies are characterized by a separation threshold α_s such that*

$$\alpha_s = \frac{1-r(W_s-\phi)}{\beta}, \tag{3}$$

and $\alpha_s \in (0, \theta_0)$.

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 leads to an eventual separation and 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 $\Pr(succ)$.

For $i \in \{s, n\}$, where s represents a successful match and n represents an unsuccessful one, let EV_i denote the expected payoff while a couple remain together. Note that EV_s is the continuation value after a successful match, whereas EV_n includes the payoff obtained while a couple remain together net of the cost of joining the platform, ϕ, but does not include the payoffs obtained from future relationships. Let σ denote the expected discounting between the beginning and end of an unsuccessful match.

The continuation value for an agent that is on the platform can be written recursively as

$$W_s = \frac{\mu}{\mu + r} \left((1 - PS) \left(EV_n + \sigma W_s \right) + PSEV_s \right), \tag{4}$$

where $\frac{\mu}{\mu+r}$ is the expected discounting until the agent is matched for the first time, and PS is the probability that a match is successful. Using this representation, we establish that there exists a unique continuation equilibrium and derive a critical level $\overline{\phi}$ such that this equilibrium is nontrivial if and only if $\phi < \overline{\phi}$. This critical level equates the agent's expected utility from paying the fee to search (once) for a new partner and the utility from remaining in a match with the worst possible fit. Let $\xi \equiv \frac{r}{\lambda}$.

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

$$\phi < \frac{\theta_0 \beta (1 + \mu \left(\lambda \xi (\xi + 2) \right)^{-1}) - 1}{\lambda \xi + \mu} \equiv \overline{\phi}. \tag{5}$$

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

$$\frac{\xi^2 + 2\xi}{\theta_0} (\lambda \xi + \lambda + \mu) \alpha_s + \frac{\mu}{\theta_0^{\xi+2}} \alpha_s^{\xi+2} = \mu \xi (\xi + 1) + \frac{\xi (\xi + 2)(\lambda (\xi + 1)(\lambda \xi \phi + \mu \phi + 1))}{\theta_0 \beta}. \tag{6}$$

3.2 The Platform's Pricing Decisions

We now study the platform's pricing problem, namely, maximizing the expected profit from each newly arriving agent, taking the agents' equilibrium behavior into account.

The platform's pricing problem is nondegenerate if there exists a strictly positive fee that induces a nontrivial continuation equilibrium. Such a fee exists if and only if $\overline{\phi}$ (see Equation (5)) is strictly positive, which occurs when

$$\theta_0\beta\mu > r\lambda^2(1-\theta_0\beta)(\lambda r+2). \tag{7}$$

Note that this condition holds when agents are sufficiently patient. In what follows, we assume that (7) holds.

By Proposition 1, if $\phi > \overline{\phi}$ then agents prefer staying in the worst possible match to returning to the platform and paying its fee. Importantly, for such fees the platform's profit would be zero. Hence, without loss of generality, we can restrict the platform's choice of fee to the closed interval $[0, \overline{\phi}]$. Finally, to ease the exposition, we also assume that the platform does not discount future payoffs.

The Platform's Pricing Problem

In order to analyze the platform's pricing problem, we first derive its profit function. The platform generates profits from the fees paid by agents who find themselves in an unsuccessful match and choose to return to the platform.[12] Thus, the platform's profit depends on the size of its repeat clientele base. This size, in turn, depends on the *conversion rate*, which is the probability that a match is successful. Note that the conversion rate is endogenous and affected by the platform's technology and pricing decisions.

Formally, we denote the conversion rate by γ and define it as

$$\gamma \equiv \Pr(\alpha < \alpha_s \mid \alpha \leq \theta_0). \tag{8}$$

On average, an agent has $\frac{1}{\gamma}$ partners, and so the platform's repeat clientele base (relative to the inflow of new users) is $(\frac{1}{\gamma}-1)$. It follows that the expected profit that the platform makes from a given agent is $(\frac{1}{\gamma}-1)\phi$. Let $\alpha_s(\phi)$ denote the solution to (6) as a function of ϕ, and let $\gamma(\phi)$ denote the induced conversion rate of matches. As there is a unique continuation equilibrium strategy for any fixed ϕ (Proposition 1), these functions are well defined. The platform's objective is thus

$$\max_{\phi\in[0,\overline{\phi}]} (\frac{1}{\gamma(\phi)} - 1)\phi. \tag{9}$$

[12]In Section 6 we consider the possibility that the platform obtains additional revenue from advertising.

Proposition 2 *The platform's pricing problem has a unique solution. It is given by*

$$\frac{1}{\gamma(\phi)} - 1 = \phi \frac{\gamma'(\phi)}{\gamma^2(\phi)}. \tag{10}$$

This optimality condition captures the central tradeoff that arises in a dynamic setting where the platform's pricing decisions determine the probability with which agents return to the platform. On the one hand, a marginal increase in ϕ increases the fee that the platform collects from each agent. Since, on average, an agent pays the fee $\frac{1}{\gamma(\phi)} - 1$ times, this direct effect is captured by the LHS of Equation (10). On the other hand, an increase in ϕ makes joining the platform less attractive and thereby increases the conversion rate $\gamma(\phi)$. Thus, an increase in ϕ decreases the average number of times that an agent pays the fee by

$$-\frac{d}{d\phi}\frac{1}{\gamma(\phi)} = \frac{\gamma'(\phi)}{\gamma^2(\phi)}.$$

As each additional round of search yields the platform a profit of ϕ, this indirect cost of increasing ϕ is captured by the RHS of Equation (10).

4 Main Results: Technology, Prices, and Profits

4.1 The Users' Response to Changes in Matching Technology

In this subsection, we use the closed-form characterization of the continuation equilibrium in order to derive comparative statics about 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 increase W_s – whether through an increase in μ or a reduction in θ_0 – increase 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. Formally, we have the following result.

Proposition 3 *Assume that (5) holds. The separation threshold α_s is increasing in ϕ and θ_0, and decreasing in μ.*

The separation threshold is a measure of equilibrium sorting: a lower α_s means that there is better sorting in the sense that agents who remain together indefinitely have a better fit. Thus, Proposition 3 implies that better technology enhances sorting, whereas a higher fee impairs sorting.

Corollary 1 *Equilibrium sorting improves due to technological improvements or a reduction in the platform's fee.*

4.2 The Effect of Technological Changes on Profits and Pricing

We start by exploring the implications of technological advances on the platform's profits (and consequently its incentives to invest in such advances).

Proposition 4 *Faster search (a higher μ) increases the platform's profits, whereas better screening (a lower θ_0) reduces its profits.*

Since the platform is a monopoly, basic economic reasoning suggests that it should benefit from an improvement in the quality of the services it provides. Proposition 4, however, establishes that technological improvements can actually *reduce* the platform's profits (although it can readjust its pricing strategy).

To grasp the intuition for this result, recall that the platform's profits depend on the size of its repeat clientele base: an increase (resp., decrease) in the size of the repeat client base shifts up (resp., down) the entire profit function. The platform's repeat clientele base is inversely related to the conversion rate. Recall that a higher speed of search makes agents more picky (Proposition 3), but has no effect on the fit of proposed matches. Thus, faster search results in a lower conversion rate and a larger repeat clientele base. On the other hand, improvements in the level of screening directly improve the fit of proposed matches and indirectly make agents more picky. The proposition shows that the direct effect is the one that dominates, and so better screening leads to an increase in the conversion rate and a smaller repeat clientele base. We can conclude that different types of technological improvements have opposite effects on the platform's profits due to their opposite effects on the size of its repeat clientele base.

Proposition 4 has clear implications for the platform's incentive to invest in its technology. To see this, consider a richer setting in which the platform can invest in improving its technology. Proposition 4 suggests that, regardless of the specific details concerning the cost and feasibility of such technological investments, the platform has neither an incentive to obtain information about its users, nor an incentive to use all of the information it does have to provide better screening (above the minimal level needed to induce a non-trivial equilibrium). On the other hand, if the cost of investing in reducing search frictions is not excessive, the platform will have an incentive to do so. These predictions are in line with the common wisdom about dating platforms: despite vast improvements in their ability to predict users' preferences using big data and machine-learning algorithms, dating platforms often still provide users with a vast number of potential matches that are unlikely to be successful.

Remark Our model assumes that the speed of search and the level of screening are independent of one another. In practice, increasing the speed of search may require the platform to compromise on its level of screening. Proposition 4 implies that, in such cases, the increase in the platform's profit resulting from faster search would be larger than it is in the current model.[13]

Technological advances alter the platform's optimal fee. Basic economic intuition suggests that better technology is associated with higher prices given the monopolistic market structure of the model. The next result establishes that this basic intuition is incorrect when consumers are patient.[14]

Proposition 5 *There exists $r^\star > 0$ such that if $r < r^\star$ then the optimal fee decreases following an improvement in the speed of search or in the level of screening.*

All else being equal, improvements in the speed of search μ increase the agents' incentive to return to the platform and search for better partners. Thus, one might think that a better search technology should lead the platform to increase its fee: intuitively, such a technological advancement counteracts the reduction in the repeat clientele base resulting from a higher fee. However, there is a second effect that may not be as transparent: the marginal effect of increasing the fee on the probability that an agent returns to the platform depends on μ. Due to the latter (potentially conflicting) effect, the optimal fee decreases following an improvement in the speed of search.

The intuition behind this result is that as μ increases, a marginal increase in ϕ leads to a greater reduction in the probability that an agent returns to the platform. In other

[13] If both the speed of search and the level of screening improve, the effect of technological changes on the platform's profit is determined by the change in the conversion rate.

[14] The assumption that agents are patient is perhaps natural when we compare the amount of time users typically spend on the platform to the amount of time they spend in a long-term relationship.

words, there is a complementarity between reducing fees and reducing search frictions on the size of the platform's repeat clientele base. Proposition 5 shows that the second effect dominates the more transparent one when agents are patient. That is, even though the repeat clientele base increases due to reduced search frictions, the platform further enhances this growth by reducing its fees.

By contrast, improvements in the level of screening reduce the likelihood that agents return to the platform (Lemma A.1). Moreover, it can be shown that the negative impact of a higher fee on the platform's repeat clientele base increases as screening improves. Thus, both the direct and indirect effects of an improvement in screening induce the platform to lower its fee.

4.3 Welfare

Combining our previous results, we arrive at the conclusion that a higher speed of search leads to a Pareto improvement. Indeed, the increase in consumer surplus due to such improvements is even amplified by the platform's response in pricing. By contrast, a higher level of screening, though it also has a positive effect on consumer welfare, is not desirable from the platform's perspective. We summarize these implications in the next corollary.

Corollary 2 *For any $r < r^{\star}$:*

- *Faster search leads to a Pareto improvement in total welfare.*
- *Better screening leads to an increase in consumer surplus and a reduction in the platform's profits.*

Corollary 2 suggests that in certain matching markets, the increasing role of online platforms may lead to underinvestment in screening technology, resulting in consumers spending a longer average time on the platform, and returning to the platform with a higher probability. This prediction reflects the tension between profits and customer goals underlying the lawsuit filed against Match Group. More broadly, it is also consistent with the phenomenon referred to as the "dating apocalypse" (Sales, 2020), where despite the growing ease of finding dating partners, it has become increasingly difficult to form a long-lasting relationship.

5 Related Literature

This paper contributes 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.[15] See Chade, Eeckhout and Smith (2017) for a comprehensive review of this literature.

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 implications of matchmakers on matching markets, they did not study the matchmaker's incentives, how they depend on technology, and how they shape the matching market outcomes.

Within the literature on marriage markets, Chade (2006) and Antler, Bird and Fershtman (2023) incorporate a learning aspect into their models.[16] 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 the agents that are active in the market appear more attractive than they actually are. Antler, Bird and Fershtman (2023) explore the effects of pre-match learning on segregation and sorting in marriage, and show that reducing search frictions can increase segregation.

In studying the implications of technological improvements on two-sided search markets, this paper is related to Eeckhout (1999), Bloch and Ryder (2000), 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 either impose a cloning assumption or consider only 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

[15] See, e.g., McNamara and Collins (1990), Morgan (1996), Burdett and Coles (1997), Eeckhout (1999), Bloch and Ryder (2000), Shimer and Smith (2000), Chade (2001, 2006), Adachi (2003), Atakan (2006), Smith (2006), Lauermann and Nöldeke (2014), Coles and Francesconi (2019), and Antler and Bachi (2022).

[16] Within 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.

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 pioneered by Caillaud and Jullien (2003), Rochet and Tirole (2003, 2006), and Armstrong (2006).[17] Much of this literature is not concerned with the process by which platform users are matched with one another.[18] However, in recent years, a literature on "matching design" has studied models where platforms match participating agents in a customized manner, with an emphasis on price discrimination (see, e.g., Gomes and Pavan, 2016, 2018; Fershtman and Pavan, 2022). In our model, the platform engages in customized matching, but in contrast to the existing literature, the customization takes the form of the platform using its information to restrict matching based on the level of fit between agents.[19]

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 clientele 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 a match is successful or not, 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.

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

[18] In particular, all users on one side of the platform interact with all users on the opposite side, and the platform, apart from influencing the participation of each side through the choice of its prices, does not actively engage in matching agents.

[19] A related literature studies how consumers' search behavior is shaped by the presence of a search engine influencing the search pool. See, e.g., Armstrong, Vickers and Zhou (2009), Athey and Ellison (2011), Chen and He (2011), Eliaz and Spiegler (2011, 2016), Hagiu and Jullien (2011), White (2013), and De Corniere (2016).

6 Concluding Remarks

Radical technological changes have turned online dating platforms into major players in two-sided matching markets. We analyzed the incentives of such platforms to harness technological advances in the speed of search and in screening the fit of proposed matches. We found that such advances increase consumer welfare, whereas, despite the monopolistic nature of the platform and its ability to readjust prices, its profits decline due to improvements in the level of screening and benefit only from improvements in the speed of search. These results imply that in a richer setting where the platform can invest in its technology, it has an incentive to invest in increasing the speed of search and a disincentive to invest in providing better screening. Thus, despite recent technological advances, it may be harder for users to find successful matches using dating platforms.

We conclude by discussing several extensions of our model and additional applications.

Asymmetry between the Two Sides of the Market

Throughout the paper, we assumed that both sides of the market are symmetric. This symmetry allowed us to simplify the exposition and present the analysis succinctly. In reality, there may be various asymmetries between both sides of the market. For instance, agents on one side of the market may be interested in long-term relationships, whereas agents on the other side of the market are more interested in short-term relationships, which can be reflected by imposing different discount factors. Alternatively, the importance of the partner's fit may vary across the two sides of the market, which can be modeled by variation in β. We now explain why introducing such asymmetries would not change our results.

In our model, the prospects of a match increase over time. As a result, agents on both sides of the market use a (side-specific) separation threshold. Since agents can terminate matches unilaterally, separation choices are driven entirely by the side with the lower separation threshold (e.g., agents who are interested in long term relationships would determine this threshold). Technically, this implies that Condition (6) (which determines the separation threshold) must be evaluated for the "pickier" side of the market. The only effect the less picky side of the market has on the analysis is that it induces an upper bound on the fee that is lower relative to the symmetric case (see Equation (5)). Given these two modifications, our analysis can be applied directly to a market with asymmetries between groups.

While the aforementioned examples of asymmetries are exogenous, the platform can artificially create asymmetry between both sides of the market by charging men and women different fees. Furthermore, the above discussion suggests that creating such asymmetries is actually profitable for the platform. To see this, suppose that rather than charging men and women the same fee ϕ, the platform charges men $\phi+\epsilon$ and women $\phi-\epsilon$. Note that the revenue per *match* from such a scheme is 2ϕ for any ϵ. This pricing scheme makes women pickier and thereby reduces the conversion rate. If ϵ is small enough such that men would rather rejoin the platform than stay single, this asymmetry enlarges the platform's repeat clientele base and thereby increases its profits.

Implications for the Labor Market

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 difference between the marriage market and the labor market in terms of modeling is in the ability to transfer utility: marriage market models typically assume that utility is nontransferable, whereas labor market models typically assume that utility is transferable (the latter assumption captures the idea that employers and potential hires can negotiate wages).

In Online Appendix C we show that the nontransferable utility model in the present paper is equivalent to a model in which agents' utility is transferable under the assumption that the flow surplus from a match is $2 \times u(\alpha, \tau)$ and that the bargaining over the surplus generated in a match is settled via the Nash bargaining solution (as is typically assumed in the literature). Thus, our results imply that job-search platforms (e.g., LinkedIn) have an incentive to invest in technologies that help match workers and employers at a faster rate, and a disincentive to invest in technologies that improve the fit of proposed matches.

Flow Subscription Fees

Online platforms often charge users a "flow" subscription fee that allows them to be active on the platform so long as they continue paying this fee (e.g., a monthly fee). Our analysis remains valid when the platform uses such a pricing policy rather than charging agents a single upfront fee that allows them to stay on the platform until they find a match, regardless of how long it takes.

The agents' separation choices depend on their expected discounted payment to the platform, and not on the exact manner in which the payment is made. Thus, whether ϕ represents an upfront payment or the expected discounted flow payments until an agent is matched is irrelevant. Furthermore, the expected cost of two such policies does not depend on the fit of matches, and hence all of the results with regard to improvements in the level of screening do not depend on the platform's pricing policy. On the other hand, an increase in the speed of search reduces the expected discounted cost of flow payments but does not alter the cost of an upfront payment. Therefore, to maintain the equivalence between the two types of pricing policies after an increase in the speed of search the platform has to increase the flow subscription fee. Since we consider the case where both the platform and the agents are patient, this modification has a similar impact on both players, and would not have a qualitative impact on our results.

In theory, a platform could use a more complex dynamic pricing policy. In particular, the firm could extract all the surplus from trade by using a two-part tariff: allow the agents to use the platform as often as they want in return for an upfront payment that equals the expected value of such matching services. This is reminiscent of "selling the firm to the agent" schemes and is rarely observed in practice as it requires agents to correctly assess the expected discounted value of receiving costless matching services in the future.

Revenue from Advertising

In our model the platform generates income only from the fees paid by its users. In practice, online platforms may generate additional income by exposing their users to advertisements. If consumers suffer a disutility from being exposed to advertising, then the choice of the level of advertising is equivalent to the choice of the fee: increasing the level of advertising is profitable for the platform and costly for consumers. If, on the other hand, consumers do not suffer any disutility from being exposed to ads, then advertising revenue increases the value of attracting repeat clientele and has no impact on consumers.[20] Due to the continuity of our model, it can be shown that all our results hold if the platform obtains a (small) flow payoff from advertising for each active user. Naturally, as the advertising revenue increases the platform's value of attracting repeat clientele, a higher advertising payoff will lead to a lower optimal fee.[21]

[20] In some cases, agents strictly benefit from being exposed to (personalized) advertisements. See, e.g., Bird and Neeman (2023) and the references therein.

[21] See proof in Antler, Bird and Fershtman (2024).

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A Proofs

Proof of Lemma 2. Equation (3) follows from a simple algebraic manipulation of the indifference condition in the main text. Thus, all we need to show is that in a nontrivial equilibrium $\alpha_s \in (0, \theta_0)$.

First, note that $\alpha_s \leq 0$ is a suboptimal choice for the agents. 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 $\alpha \in [0, \frac{1-\mu/(\mu+r)}{\beta})$.

Finally, note that if $\alpha_s \geq \theta_0$, then agents accept proposed matches with probability one, and so the resulting equilibrium is trivial. ■

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 $\alpha_s < \theta_0$, and at the end of this part of the proof we verify that this inequality holds under Condition (5).

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 (4) 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 $\theta_t > \alpha$ and is constant thereafter. Integrating (1) yields

$$\theta_t = e^{-\lambda t}\theta_0,$$

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

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

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

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

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

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

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

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

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

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

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

$$\sigma = E\left(e^{-rT_m(\alpha)} | \alpha \sim U[\alpha_s, \theta_0]\right) = \frac{\lambda \left(\theta_0 - \alpha_s \left(\frac{\alpha_s}{\theta_0}\right)^{r/\lambda}\right)}{(\theta_0 - \alpha_s)(\lambda + r)}. \tag{A.4}$$

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

$$PS = \frac{\alpha_s}{\theta_0}, \tag{A.5}$$

and by (3) we have that

$$W_s = \frac{1 - \alpha_s \beta}{r} + \phi. \tag{A.6}$$

Plugging (A.2)–(A.6) into Equation (4) and rearranging yields Equation (6).

Existence and Uniqueness. To see that the nontrivial equilibrium, if it exists, is unique, note that the LHS of Condition (6) is 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 $\alpha_s \in (0, \theta_0)$ that solves Equation (6). The RHS of Equation (6) is strictly positive and independent of α_s. On the other hand, the LHS of Equation (6) is increasing in α_s and equals zero if evaluated at $\alpha_s = 0$. Therefore, a nontrivial equilibrium exists if the LHS that is evaluated at the maximum value of α_s, namely, θ_0, yields a term that is greater than the RHS, that is, if

$$\mu + \xi(\xi+2)(\lambda\xi + \lambda + \mu) > \frac{\lambda\xi(\xi+2)(\xi+1)(\lambda\xi\phi + \mu\phi + 1)}{\theta_0\beta} + \mu\xi(\xi+1), \tag{A.7}$$

a condition that is equivalent to (5). 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 (6). That is, if (A.7) is satisfied, there is no trivial equilibrium.

Finally, consider the trivial equilibrium. In the trivial equilibrium agents terminate a match with probability zero. The previous analysis shows that if (5) does not hold, then an agent prefers staying in a match of fit θ_0 to terminating the match and paying ϕ to return to the platform. By Assumption (7), an agent is better off staying in any match than terminating it and remaining single. Therefore, if (5) does not hold there is only a trivial equilibrium in which agents never terminate a match. ■

Proof of Proposition 2. Note that $\alpha_s(\phi)$ is a differentiable function. The platform therefore maximizes a differentiable profit function over a closed interval, and hence there is an optimal fee that is given by a first-order condition. Furthermore, as the platform's profit from setting a fee of either 0 or $\overline{\phi}$ is zero, the optimal fee is interior and the first-order condition holds with equality.

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

$$\pi'(\phi) = \frac{\theta_0}{\alpha_s(\phi)} - 1 - \phi\frac{\theta_0\alpha_s'(\phi)}{\alpha_s(\phi)^2}. \tag{A.8}$$

Thus, an optimal fee must satisfy

$$\frac{\theta_0}{\alpha_s(\phi)} - 1 - \phi\frac{\theta_0 \alpha_s'(\phi)}{\alpha_s(\phi)^2} = 0,$$

a condition that is equivalent to Equation (10).

Next, we show that the firm's profit is concave in ϕ. Implicit differentiation of Equation (6) yields

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

Thus, Equation (A.8) can be written as

$$\pi'(\phi) = \frac{\gamma(\phi) - \frac{\xi(\xi+1)\phi(\mu+\xi)}{\theta_0\beta\left(\mu\gamma(\phi)^{\xi+1}+\xi(\mu+\xi+1)\right)}}{\gamma(\phi)^2} - 1.$$

The second derivative of π is given by

$$\pi''(\phi) = \frac{\xi(1+\xi)(\mu+\xi)}{\theta_0^2\beta^2\left(\mu\gamma^{\xi+2}+\gamma\xi(\mu+\xi+1)\right)^3}\times$$
$$\left(\xi(\xi+1)\phi(\mu+\xi)\left(\mu(\xi+3)\gamma^{\xi+1}+2\xi(\mu+\xi+1)\right) - 2\theta_0\beta\gamma\left(\mu\gamma^{\xi+1}+\xi(\mu+\xi+1)\right)^2\right),$$

where, to ease the exposition, we have normalized $\lambda = 1$. From Equation (6) it follows that

$$\phi = \frac{\frac{\theta_0\beta\left(\mu\gamma^{\xi+2}+\gamma\xi(\xi+2)(\mu+\xi+1)-\mu\xi(\xi+1)\right)}{\xi(\xi^2+3\xi+2)} - 1}{\mu+\xi}. \tag{A.9}$$

Plugging this expression into $\pi''(\phi)$ and rearranging yields

$$\pi''(\phi) = \frac{\xi(1+\xi)(\mu+\xi)}{\theta_0^2\beta^2\left(\mu\gamma^{\xi+2}+\gamma\xi(\mu+\xi+1)\right)^3}\times$$
$$\Bigg(-\mu\xi(\xi+2)(\xi+3)\gamma^{\xi+1} - 2\xi^3(\mu+\xi+1) - 4\xi^2(\mu+\xi+1)$$
$$+\theta_0\beta\left\{-\mu^2\gamma^{2\xi+3}+\mu\xi\gamma^{\xi+1}(\mu((\gamma-1)\xi-3)+\gamma\xi(\xi+1)) - 2\mu\xi^2(\mu+\xi+1)\right\}\Bigg).$$

Note that the sign of this second derivative is given by the sign of the term in large brackets. If the term in curly brackets is negative, then the second derivative is negative. Otherwise, the second derivative is increasing in $\theta_0\beta$ and so it is sufficient to show that the second derivative is negative at the upper bound of $\theta_0\beta$, namely, $\theta_0\beta = 1$. Evaluating the term in large brackets at $\theta_0\beta = 1$ yields

$$-\mu^2\gamma^{2\xi+3} + \mu\xi^2\gamma^{\xi+2}(\mu+\xi+1) - \mu\xi(\xi+3)\gamma^{\xi+1}(\mu+\xi+2) - 2\xi^2(\mu+\xi+1)(\mu+\xi+2) <$$
$$-\mu^2\gamma^{2\xi+3} + \mu\xi^2\gamma^{\xi+1}(\mu+\xi+1) - \mu\xi(\xi+3)\gamma^{\xi+1}(\mu+\xi+2) - 2\xi^2(\mu+\xi+1)(\mu+\xi+2)$$
$$= -\mu^2\gamma^{2\xi+3} - \mu\xi\gamma^{\xi+1}(3\mu+4\xi+6) - 2\xi^2(\mu+\xi+1)(\mu+\xi+2) < 0,$$

where the first inequality follows from the fact that $\gamma < 1$.

Since $\pi''(\phi) < 0$, the profit function is concave and it has a unique maximum. ■

Proof of Proposition 3. From Equation (3) it follows that α_s is decreasing in W_s. To prove this proposition we show that, under Condition (5), W_s is increasing in μ and decreasing in θ_0 and ϕ.

Due to the symmetry of the model and, in particular, the symmetry of the agents' equilibrium strategies, comparative statics for this model can be analyzed as if it were a decision problem. By Condition (5), an agent's optimal strategy is interior and satisfies a first-order condition. Hence, the envelope theorem applies, and so the impact of marginal changes in model parameters on an agent's payoff can be evaluated by how such a change alters the agent's payoff under the original equilibrium strategy.

Fixing an agent's strategy, payoffs in a nontrivial equilibrium are decreasing in ϕ as the fee is paid with positive probability. Payoffs are also decreasing in θ_0 since increasing θ_0 decreases the payoff from any given match. Finally, since an agent does not receive payoffs while single and receives positive payoffs while in a match, increasing the speed of search increases the payoffs from the equilibrium strategies. ■

Proof of Proposition 4. The platform's profit curve (9) is decreasing in the conversion rate. In Lemma A.1 below, we establish that, holding ϕ fixed, the conversion rate is decreasing in both μ and θ_0. Hence, by a standard revealed preference argument, improvements in the speed of search (an increase in μ) increase the platform's profit, whereas improvements in the level of screening (a decrease in θ_0) decrease its profit. ■

Lemma A.1 *Assume that Condition (5) holds. The conversion rate γ is decreasing in μ and increasing in θ_0.*

Proof. Since α_s is decreasing in μ (Proposition 3), it follows that $\gamma = \frac{\alpha_s}{\theta_0}$ is also decreasing in μ. To derive the second part of this result, perform the replacement $\alpha_s = \gamma\theta_0$ in Equation (6). This yields the following implicit characterization of the conversion rate:

$$\mu\gamma^{\xi+2} + \gamma\xi(\xi+2)(\lambda\xi+\lambda+\mu) = \frac{\xi(\xi+2)(\lambda(\xi+1)(\lambda\xi\phi+\mu\phi+1))}{\theta_0\beta} + \mu\xi(\xi+1). \quad \text{(A.10)}$$

Note that the RHS of (A.10) is decreasing in θ_0 and independent of γ, whereas the LHS of (A.10) is increasing in γ and independent of θ_0. It follows that γ is decreasing in θ_0. ■

Proof of Proposition 5. To establish this result, we consider separately improvements in μ and in θ_0.

Faster search— By Proposition 2, the platform's optimal fee is given by equating the first-order condition (A.8) to zero. Rearranging this equality yields:

$$-\theta_0\phi\alpha_s^{(1,0,0)}(\phi,\mu,\theta_0) - \alpha_s(\phi,\mu,\theta_0)^2 + \theta_0\alpha_s(\phi,\mu,\theta_0) = 0, \quad \text{(A.11)}$$

where $\alpha_s(\phi,\mu,\theta_0)$ denotes the solution to (6) as a function of ϕ, μ, and θ_0 and $\alpha_s^{(\mathbf{I}_\phi,\mathbf{I}_\mu,\mathbf{I}_{\theta_0})}(\phi,\mu,\theta_0)$ is the partial derivative of $\alpha_s(\phi,\mu,\theta_0)$ with respect to all $x \in \{\phi,\mu,\theta_0\}$ for which $\mathbf{I}_x = 1$. To establish the first part of the proposition, we show that the derivative of the LHS of this first-order condition (A.11) with respect to μ is negative when agents are sufficiently patient.

Recall that implicit differentiation of Equation (6) yields

$$\alpha_s'(\phi) = \frac{\theta_0\lambda\xi(\xi+1)(\lambda\xi+\mu)}{\alpha_s\beta\mu\left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0\beta\xi(\lambda\xi+\lambda+\mu)},$$

whereas solving Equation (6) for ϕ yields

$$\phi = \frac{\alpha_s^2\beta\mu\left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0\alpha_s\beta\xi(\xi+2)(\lambda\xi+\lambda+\mu) - \theta_0\xi(\xi+1)(\theta_0\beta\mu+\lambda(\xi+2))}{\theta_0\lambda\xi\left(\xi^2+3\xi+2\right)(\lambda\xi+\mu)}.$$

Plugging these expressions into the first-order condition (A.11), and evaluating it at $r = 0$, yields

$$\frac{1}{2}(\theta_0 - 2\alpha_s)\alpha_s.$$

It follows that, under the optimal fee, $\alpha_s \to \frac{\theta_0}{2}$ as r converges to zero.

The derivative of the LHS of the first-order condition (A.11) with respect to μ is

$$(\theta_0 - 2\alpha_s(\phi, \mu, \theta_0))\alpha_s^{(0,1,0)}(\phi, \mu, \theta_0) - \theta_0 \phi \alpha_s^{(1,1,0)}(\phi, \mu, \theta_0). \tag{A.12}$$

Implicit differentiation of (6) yields

$$\alpha_s^{(0,1,0)}(\phi, \mu, \theta_0) = \frac{\theta_0 \xi(\xi+1)(\theta_0\beta + \lambda(\xi+2)\phi) - \alpha_s^2 \beta \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} - \theta_0 \alpha_s \beta \xi(\xi+2)}{\beta(\xi+2)\left(\alpha_s \mu \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0 \xi(\lambda\xi + \lambda + \mu)\right)},$$

which, in turn, yields

$$\begin{aligned}\alpha_s^{(1,1,0)}(\phi, \mu, \theta_0) = {} & \frac{\theta_0 \lambda \xi(\xi+1)}{\beta(\xi+2)\left(\alpha_s \mu \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0 \xi(\lambda\xi + \lambda + \mu)\right)^2 \left(\alpha_s \beta \mu \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0 \beta \xi(\lambda\xi + \lambda + \mu)\right)} \times \\ & \left(\mu(\xi+1)\left(\frac{\alpha_s}{\theta_0}\right)^{\xi}(\lambda\xi + \mu)\left(\alpha_s^2 \beta \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0 \alpha_s \beta \xi(\xi+2) - \theta_0 \xi(\xi+1)(\theta_0 \beta + \lambda(\xi+2)\phi)\right)\right. \\ & \left. + \beta\lambda\xi(\xi+2)\left(\theta_0 - \alpha_s\left(\frac{\alpha_s}{\theta_0}\right)^{\xi}\right)\left(\alpha_s \mu \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0 \xi(\lambda\xi + \lambda + \mu)\right)\right).\end{aligned}$$

Normalizing $\lambda = 1$, plugging the above derivatives into (A.12), and evaluating it at $\alpha_s = \frac{\theta_0}{2}$ yields

$$\begin{aligned} & \frac{-r}{2\theta_0 \beta^2 (r+2)^2 (\mu + r)\left(\mu + 2^{r+1} r(\mu + r + 1)\right)^3} \times \\ & \left(\theta_0 \beta \mu + 2^{r+1} r((r+1)(r+2)(\theta_0 \beta - 2) - \theta_0 \beta \mu r)\right) \times \\ & \left(-\theta_0 \beta \mu + \theta_0 \beta 4^{r+1} r(r+2)(\mu + r + 1) - 2^{r+1}\left(2\theta_0 \beta \mu r(r(r+3)+3) + \theta_0 \beta r(r+2)(r+1) - 2\mu(r+2)(r+1)^2\right)\right).\end{aligned}$$

The first term of the above product is negative. Thus, to evaluate the sign of this cross-derivative as agents become patient, it is sufficient to evaluate the product of the latter two terms when $r \to 0$. Doing so yields

$$\theta_0 \beta \mu^2 (8 - \theta_0 \beta) > 0,$$

where the inequality follows from Assumption 2. That is, the cross-derivative of the profit with respect to μ and ϕ is negative when agents are patient. Due to the continuity of the model in r, there exists $r_1^\star > 0$ such that if $r < r_1^\star$, then (A.12) is negative. This completes the first part of the proof.

Better screening— The optimal fee is determined by the solution of the first-order condition (A.11), which can also be written as

$$-\phi\alpha_s^{(1,0,0)}(\phi,\mu,\theta_0) - \frac{\alpha_s(\phi,\mu,\theta_0)^2}{\theta_0} + \alpha_s(\phi,\mu,\theta_0). \tag{A.11a}$$

Differentiating this representation of the first-order condition with respect to θ_0 yields

$$\frac{\alpha_s(\phi,\mu,\theta_0)\left(\alpha_s(\phi,\mu,\theta_0) - 2\theta_0\alpha_s^{(0,0,1)}(\phi,\mu,\theta_0)\right)}{\theta_0^2} + \alpha_s^{(0,0,1)}(\phi,\mu,\theta_0) - \phi\alpha_s^{(1,0,1)}(\phi,\mu,\theta_0). \tag{A.13}$$

To show that this derivative is positive, we follow the same steps as in the first part of the proof: we use implicit differentiation of (6) to calculate the derivatives of α_s, use (A.9) to replace ϕ, normalize $\lambda = 1$, use the change of variable $\alpha_s = \gamma\theta_0$, and evaluate the resulting condition at $r = 0$ and $\gamma = \frac{1}{2}$.

By implicit differentiation of (6) we have that

$$\alpha_s^{(0,0,1)}(\phi,\mu,\theta_0) = \frac{\alpha_s}{\theta_0} - \frac{\lambda\xi(\xi+1)(\lambda\xi\phi+\mu\phi+1)}{\alpha_s\beta\mu\left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0\beta\xi(\lambda\xi+\lambda+\mu)},$$

and that

$$\alpha_s^{(1,0,1)}(\phi,\mu,\theta_0) = \frac{\theta_0\lambda^2\mu\xi^2(\xi+1)^3\left(\frac{\alpha_s}{\theta_0}\right)^{\xi}(\lambda\xi+\mu)(\lambda\xi\phi+\mu\phi+1)}{\beta^2\left(\alpha_s\mu\left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0\xi(\lambda\xi+\lambda+\mu)\right)^3}.$$

Plugging these two expressions into (A.11a), using the change of variable $\alpha_s = \gamma\theta_0$, normalizing $\lambda = 1$, and rearranging yields

$$\begin{aligned}\gamma - \gamma^2 - &\frac{\theta_0\lambda^2\mu r^2(r+1)^3\phi\gamma^r(\mu+\lambda r)(\mu\phi+\lambda r\phi+1)}{\beta^2\left(\theta_0\mu\gamma^{r+1}+\theta_0 r(\lambda+\mu+\lambda r)\right)^3}\\ &+ \frac{2\gamma\lambda r(r+1)(\mu\phi+\lambda r\phi+1)}{\theta_0\beta\mu\gamma^{r+1}+\theta_0\beta r(\lambda+\mu+\lambda r)} - \frac{\lambda r(r+1)(\mu\phi+\lambda r\phi+1)}{\theta_0\beta\mu\gamma^{r+1}+\theta_0\beta r(\lambda+\mu+\lambda r)}.\end{aligned} \tag{A.14}$$

Finally, plugging (A.9) into (A.14) and evaluating the resulting condition at $r = 0$ and $\gamma = \frac{1}{2}$ yields $\frac{1}{8}$. That is, the cross-derivative of profit with respect to θ_0 and ϕ is positive when agents are patient. By continuity, there exists $r_2^\star > 0$ such that if $r < r_2^\star$ then the marginal value of increasing ϕ increases with θ_0. Thus, better screening – i.e., a decrease in θ_0 – leads to a reduction in the optimal fee.

The proposition is established for $r^\star = \min\{r_1^\star, r_2^\star\}$. ■

B Online Appendix: Quadratic Search

In this appendix we show that the main results of the paper hold if the search technology is quadratic (rather than linear). That is, in this appendix we assume that the rate at which an agent meets potential partners is given by νM^*, where M^* is the steady-state mass of agents on each side of the platform, and $\nu > 0$ measures the speed of search. Throughout the appendix, we assume that if there exist both a trivial and a nontrivial equilibrium, the latter will be played. Except for this selection assumption, all of the modeling assumptions remain as in the main text.

B.1 Steady-State Equilibrium

In this appendix, we use steady-state equilibrium as our solution concept. In a steady-state equilibrium, the platform specifies a fee, $\phi \geq 0$, and agents respond to this choice by selecting the optimal stationary strategy, α_s. Finally, in a steady-state equilibrium, the measure of agents that are active on the platform must be consistent with the agents' strategies and must not change over time. That is, the flows into and out of the platform must be balanced and the measure of agents that are active on the platform must not change over time.

The outflow of agents from the platform is equal to the measure of meetings

$$OF = \nu(M^*)^2.$$

The inflow of agents is the sum of the exogenous arrival of new agents and the measure of agents that terminate their match and return to the platform. As a match results in eventual termination with probability $1 - \frac{\alpha_s}{\theta_0}$, the inflow is given by

$$IF = \eta + (1 - \frac{\alpha_s}{\theta_0})\nu(M^*)^2.$$

In the steady state, the inflow equals the outflow. Hence, the steady-state measure of agents that are active in the platform can be found by solving $IF = OF$, which yields

$$M^* = \sqrt{\frac{\theta_0 \eta}{\alpha_s \nu}}.$$

B.2 Agents' Behavior

The agents' behavior characterized in Equation (6) was derived under the assumption that an agent meets potential partners at rate μ. In the steady state of the model with quadratic search technology the meeting rate of a given agent is νM^*. Replacing μ with νM^* in Equation (6) and rearranging yields

$$\frac{\frac{\sqrt{\eta}\sqrt{\nu}\left(\alpha_s^2 \beta \left(\frac{\alpha_s}{\theta_0}\right)^{\xi} + \theta_0 \alpha_s \beta \xi(\xi+2) - \theta_0 \xi(\xi+1)(\theta_0 \beta + \lambda(\xi+2)\phi)\right)}{\sqrt{\alpha_s}} + \sqrt{\theta_0}\lambda \xi(\xi+1)(\xi+2)(\alpha_s \beta - \lambda \xi \phi - 1)}{\theta_0^{3/2}\beta} = 0. \tag{B.1}$$

Using the change of variable $\alpha_s = \gamma \theta_0$ in Equation (B.1) and rearranging yields that the equilibrium behavior is characterized by the root of

$$\begin{aligned} F = \theta_0 \sqrt{\eta}\sqrt{\nu}\left(\theta_0 \beta \left(\gamma^{\xi+2} + \gamma \xi(\xi+2) - \xi(\xi+1)\right) - \lambda \xi(\xi+1)(\xi+2)\phi\right) \\ + \theta_0 \sqrt{\gamma} \lambda \xi(\xi+1)(\xi+2)(\theta_0 \beta \gamma - \lambda \xi \phi - 1). \end{aligned} \tag{B.2}$$

Next we show that this equation has at most one positive root; i.e., there cannot exist multiple nontrivial equilibria. The second derivative of F with respect to γ is

$$\frac{\partial^2 F}{\partial^2 \gamma} = \frac{(\xi+1)(\xi+2)\left(4\theta_0 \beta \sqrt{\eta}\sqrt{\nu}\gamma^{\xi+\frac{3}{2}} + \lambda \xi(3\theta_0 \beta \gamma + \lambda \xi \phi + 1)\right)}{4\gamma^{3/2}} > 0,$$

and evaluating F at $\gamma = 0$ yields

$$-\sqrt{\eta}\sqrt{\nu}\xi(\xi+1)(\theta_0 \beta + \lambda(\xi+2)\phi) < 0.$$

That is, F is a convex function that is negative at $\gamma = 0$, and so it can have at most one positive root.

This root represents a nontrivial equilibrium if it is less than 1 (as $\gamma \in (0,1)$ in a nontrivial equilibrium). Since F is convex and negative at zero, its root is less than one if and only if F evaluated at $\lambda = 1$ is strictly positive. This occurs if

$$\phi < \overline{\phi_q} \equiv \theta_0\beta\left(\sqrt{\eta}\sqrt{\nu} + \lambda\xi(\xi+2)\right) - \lambda\xi(\xi+2).$$

If $\phi \geq \overline{\phi_q}$, then the only equilibrium is the trivial one. However, unlike the baseline model, if $\phi < \overline{\phi_q}$, there can be both a trivial and a nontrivial equilibrium. Intuitively, if all agents accept their initial partner, the matching rate on the platform goes down, which, in turn justifies an agent's decision to remain with their initial partner. Recall that it is assumed that if a nontrivial equilibrium exists, then this is the equilibrium that will be played. Under this selection assumption, the above analysis replicates Proposition 1 for the quadratic search technology.

B.3 The Platform's Pricing Problem

To make the platform's problem nondegenerate, for the rest of this section we assume that $\overline{\phi_q} > 0$. That is, we assume that

$$\theta_0\beta\left(\sqrt{\eta}\sqrt{\nu} + \lambda\xi(\xi+2)\right) > \lambda\xi(\xi+2).$$

As in the baseline model, setting a fee of zero or $\overline{\phi_q}$ is suboptimal. Moreover, the platform's first-order condition derived in the main model depends on the search technology directly only through its effect on γ, and so the characterization of the the platform's optimal fee provided in Equation (10) remains valid. In the case of quadratic search technology, we show that the optimal fee is unique only in the case where agents are patient. The marginal profit from increasing ϕ is still given by Equation (A.8); however, under quadratic search,

$$\alpha_s'(\phi) = \frac{2\theta_0\sqrt{\gamma}\lambda\xi(\xi+1)\left(\sqrt{\gamma}\lambda\xi + \sqrt{\eta}\sqrt{\nu}\right)}{\theta_0\beta\left(2\sqrt{\eta}\sqrt{\nu}\gamma^{\xi+\frac{3}{2}} + 2\sqrt{\gamma}\sqrt{\eta}\sqrt{\nu}\xi + 3\gamma\lambda\xi(\xi+1)\right) - \lambda\xi(\xi+1)(\lambda\xi\phi+1)}. \quad \text{(B.3)}$$

Moreover, under quadratic search and the normalization of $\lambda = 1$ we have that

$$\phi = -\frac{-\theta_0\beta\sqrt{\eta}\sqrt{\nu}\left(\gamma^{\xi+2} + \gamma\xi(\xi+2) - \xi(\xi+1)\right) - \theta_0\beta\gamma^{3/2}\xi(\xi+1)(\xi+2) + \sqrt{\gamma}\xi(\xi+1)(\xi+2)}{\xi(\xi+1)(\xi+2)\left(\sqrt{\gamma}\xi + \sqrt{\eta}\sqrt{\nu}\right)}. \quad \text{(B.4)}$$

Plugging $\alpha_s'(\phi)$ into Equation (A.8), differentiating with respect to ϕ, normalizing $\lambda = 1$, and plugging in the expression for ϕ derived in (B.4) and $\xi = 0$ yields

$$-\frac{1}{4\theta_0\beta\gamma^3\sqrt{\eta}\sqrt{\nu}}.$$

That is, the platform's profit function is concave when agents are patient. Thus, we have reestablished Proposition 2 in the case where agents are patient.

B.3.1 The conversion rate

Recall that the platform's profit curve is $(\frac{1}{\gamma} - 1)\phi$, and thus to determine the effect of technological advances on the platform's profit, we show how the conversion rate depends on the platform's technology. To this end, it is more convenient to characterize the equilibrium conversion rate by the roots of $G = \frac{F}{\theta_0\beta\sqrt{\gamma}}$. The partial derivatives of G are given by

$$\begin{aligned}
\frac{\partial G}{\partial \gamma} &= \frac{\theta_0^{3/2}\sqrt{\eta}\sqrt{\nu}\left((2\xi+3)\gamma^{\xi+2} + \gamma\xi(\xi+2) + \xi^2 + \xi\right)}{2(\theta_0\gamma)^{3/2}} \\
&\quad + \frac{\sqrt{\theta_0}\sqrt{\eta}\lambda\sqrt{\nu}\xi(\xi+1)(\xi+2)\phi}{2\beta(\theta_0\gamma)^{3/2}} + \lambda\xi(\xi+1)(\xi+2), \\
\frac{\partial G}{\partial \theta_0} &= \frac{\lambda\xi(\xi+1)(\xi+2)\left(\sqrt{\theta_0\gamma}(\lambda\xi\phi+1) + \sqrt{\theta_0}\sqrt{\eta}\sqrt{\nu}\phi\right)}{\theta_0^2\beta\sqrt{\theta_0\gamma}}, \\
\frac{\partial G}{\partial \nu} &= \frac{\sqrt{\eta}\left(\theta_0\beta\left(\gamma^{\xi+2} + \gamma\xi(\xi+2) - \xi(\xi+1)\right) - \lambda\xi(\xi+1)(\xi+2)\phi\right)}{2\sqrt{\theta_0}\beta\sqrt{\nu}\sqrt{\theta_0\gamma}}.
\end{aligned}$$

Note that $\frac{\partial G}{\partial \gamma}, \frac{\partial G}{\partial \theta_0} > 0$, and so implicit differentiation of $G = 0$ yields $\frac{\partial \gamma}{\partial \theta_0} < 0$. That is, better screening – i.e., a reduction in θ_0 – increases the conversion rate. To show that the conversion rate is decreasing in ν it is enough to show that $\frac{\partial G}{\partial \nu} > 0$. That is, we must show that

$$\theta_0\beta\left(\gamma^{\xi+2} + \gamma\xi(\xi+2) - \xi(\xi+1)\right) - \lambda\xi(\xi+1)(\xi+2)\phi > 0. \tag{B.5}$$

Since in equilibrium $G = 0$, we have that

$$\phi = \frac{\lambda\xi\sqrt{\theta_0\gamma}\left(\theta_0\beta\gamma^{\xi+2} - \theta_0\beta\left(\gamma(\xi+2) + \xi^2 + \xi\right) + (\xi+1)(\xi+2)\right)}{\lambda\xi\sqrt{\theta_0\gamma} + \sqrt{\theta_0}\sqrt{\eta}\sqrt{\nu}}. \tag{B.6}$$

Plugging (B.6) into (B.5) and rearranging yields

$$\theta_0\beta\gamma^{\xi+2} - \theta_0\beta\left(\gamma(\xi+2)+\xi^2+\xi\right)+(\xi+1)(\xi+2) > 0. \tag{B.7}$$

Since $\gamma < 1$ and $\xi > 0$, the LHS of Equation (B.7) is decreasing in γ. Thus, to establish that (B.7) holds it is sufficient to show that it holds at $\gamma = 1$, that is, to show that

$$(\xi+1)(1+(1+\xi)(1-\theta_0\beta)) > 0,$$

an inequality that holds by Assumption 2, which stipulates that $\beta\theta_0 < 1$. Thus, we have established Lemma A.1 in the case of a quadratic search technology.

This analysis shows that improvements in the speed of search – an increase in ν – leads to an upward shift of the profit curve, whereas improvements in the level of screening – a reduction in θ_0 – leads to a downward shift of the entire profit curve. This establishes Proposition 4 in the case of a quadratic search technology.

B.3.2 Technology and Pricing

This subsection establishes that technological improvements lead to lower prices. The platform's first-order condition (A.11) is the same under quadratic search. Plugging (B.3) and (B.4) into this first-order condition, normalizing $\lambda = 1$, and evaluating the first-order condition yields $\frac{1}{2}\alpha_s(\theta_0 - 2\alpha_s)$. That is, just like under a linear search technology, the optimal conversion rate is $\frac{1}{2}$ when agents are patient.

To establish the effect of technological advances on pricing we proceed in the same manner as in the baseline model. We use implicit differentiation of Equation (B.1) to calculate the derivatives and cross-derivatives of α_s. We then use these derivatives and (B.4) to sign the cross-derivatives of the platform's profit at $r = 0, \gamma = \frac{1}{2}$. Doing so yields that the sign of $\frac{\partial^2\pi}{\partial\phi\partial\nu}$ is equal to the sign of

$$-\frac{\theta_0\beta+8}{32\sqrt{2}\beta\sqrt{\eta}\nu^{3/2}} < 0,$$

whereas the sign of $\frac{\partial^2\pi}{\partial\phi\partial\nu}$ is equal to the sign of $\frac{1}{8}$. That is, both faster search and better screening – an increase in ν and a reduction in θ_0, respectively, – decrease the marginal value of increasing ϕ. That is, technological advances lead to a reduction in the optimal fee, as established by Proposition 5 for a linear search technology.

C 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 modify the model by assuming that couples can transfer utility in order to make it suitable to analyze interactions in the labor market. We then show that the two models are formally equivalent.

Let us modify the model such that while agents x and y are together for τ units of time, they generate a flow payoff of $2(1 - \beta \cdot \max\{\alpha(x, y), \theta_\tau\})$, where $\alpha(x, y)$ and β are 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 6 *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 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. ■