Selling Roses on Online Dating Platforms

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Problem Definition. Dating apps offer users the opportunity to match with potential partners, but the mechanisms through which this opportunity is monetized, what is free and what is offered at cost, vary widely across platforms. Many popular dating apps in the United States generate revenue by offering suites of virtual products that increase a user's chances of matching. These products may improve candidate recommendations based on private platform data (e.g. *Tinder's* Top Picks), expand the users range of matches by displaying their profile to others at a higher rate (e.g. *Bumble's* Boost), or increase visibility to one specific potential match of interest (e.g. *Hinge's* Roses). We investigate this final category of virtual products, which we refer to as roses, and consider how they should be implemented and offered to users.

Methodology / Results. In a multi-period model with forward-looking customers, we consider three selling mechanisms: offering roses separately in each period, offering a bundle of roses only in the first period, and offering a menu of both options. Under each mechanism we characterize the utility-maximizing user behavior and derive the revenue-maximizing pricing and design for offering roses. In each case, we find that increasing the efficacy of the rose (and then appropriately pricing them) monotonically increases platform revenue. Further, under these maximal roses, we find that offering them separately in each period dominates the revenue, user surplus, and social welfare of bundle selling and is nearly equal to more involved mixed mechanism across all three metrics.

Managerial Implications. Our results yield actionable guidelines for the design and monetization of dating apps. In particular, when the platform offers maximally effective roses, the system reduces to an a la carte where users can only message via a rose. Thus our work lends support for pay-to-message platforms like *Match.com* as a platform design choice that can increase both revenue and user welfare.

Key words. Roses, Digital Goods, Online dating, Pricing, Bundling,

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This is a work in progress

1. Introduction

Online dating apps such as Bumble, Tinder, and Hinge have become the primary medium through which American adults form new romantic relationships (Rosenfeld et al. 2019). These apps help users meet potential dating partners and facilitate initial communication between them. Nearly 40% of people between the ages of 18 and 30 meet their partners online, and more than half of Americans find that relationships that begin on a dating site are just as successful as those that begin in person (Anderson et al. 2020). Globally,

revenue in the online dating market is projected to reach $3.17 billion in 2025, and the number of users is estimated to reach $462.5 million by 2029 (Statista 2023).

The most common type of dating app is a so-called *swipe app* where a sequence of candidates is generated for each user by the app, and the user is asked to express their preference over the candidates by swiping right (to accept) or left (to reject). When a user expresses interest by swiping right, the candidate receives a notification and then considers establishing a match and engaging in further communication (see Fig. EC.3 for a depiction). To enhance matching efficiency and revenue, many dating apps offer pay-per-use services designed to let a user indicate exceptional interest in a particular candidate and increase the user's chance of matching with them. For instance, *Hinge* offers "Roses" that allow users to express a strong interest in a specific candidate match, and be boosted to the top of the candidates swipe queue. Similarly, *Tinder* uses "Super Likes", while *Bumble* utilizes "SuperSwipes", both of which allow a user to increase their visibility, and thus matching probability, with a specific candidate for one a one-time cost. For depictions of "Roses", 'Super Likes", and "SuperSwipes" in practice, see Fig. 1, and for a depiction and additional discussion of how these products function see Fig. EC.4 in the appendix.

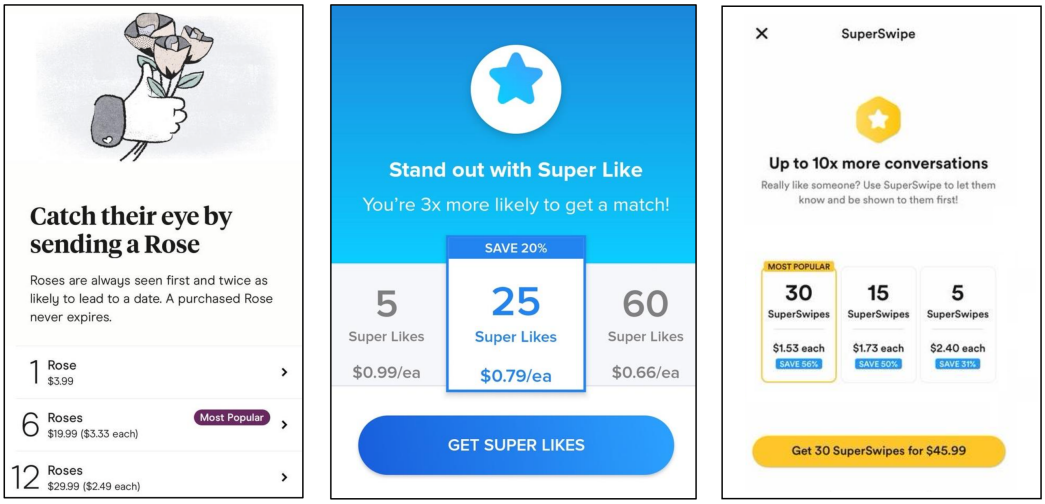


Figure 1 **Examples of rose-like products on dating apps.** Depicted are three examples of pay-per-use products on popular dating apps. On the left is the pricing for "Roses" on *Hinge*, where a rose can be attached with a message, and increases the likelihood of the associated message being seen by the recipient. Similar products are also depicted, including *Tinder's* "Super Like" (middle) and *Bumble's* "SuperSwipe" (right).

In this paper, we will study the design and pricing of these match enhancing products, which we will refer to as *roses* throughout[1]. In online dating apps, roses are generally sold either as individual units or in bundled packages, as depicted in Fig. 1. Moreover, rose-like products vary in their efficacy, with some guaranteeing

[1] We emphasize that this paper places no special emphasis on *Hinge's* match enhancing products. The use of the term roses is our preference.

visibility by placing the user at the top of the recipients swipe queue, whiles others merely claim to increase the probability of matching.

Fig. 1 also provides a direct example of the different design strategies across online dating platforms, parallel to what we study in this paper. The first platform (Hinge) is the only one among the three that incorporate a separate selling strategy in their general strategy and offers a single rose that is the most expansive compared to other platforms, signaling a higher effectiveness and a more valuable rose. The second platform (Tinder) only offers bundle of roses with a low price per rose, signaling lower effectiveness of a rose hand to hand with a stronger appeal among the users to buy roses making acquiring a match hard for the users who do not send roses. Finally, the third platform (Bumble), similar to Tinder, does not offer a single rose to the users but offers them in bundles with higher prices which again signals a more effective rose design. We will study the optimal selling strategy and effectiveness later in this paper alongside the relationships between revenue, price, effectiveness and search costs, trying to introduce a general strategy in selling roses in the online dating platforms.

Abstractly, a dating app offering roses must set two parameters: the price for the rose, or a bundle of the roses, and some measure of the roses effectiveness. Specifically, by purchasing and using a rose, the user will increase their chance of getting shown to a candidate and securing a match. We name this boosting effect of the rose as $\delta > 0$, and model it as an increase in the probability of matching by a factor of $(1 + \delta)$. For a profit-maximizing dating app in designing roses, and particularly setting δ, is complex. While a larger δ makes the rose more valuable to users, and thus can potentially be sold at a higher price, by increasing the chance of matching it may also increase user churn (as users match and leave the platform) reducing the potential for future profit.

Motivated by this complexity, we study several different rose selling strategies, such as separate selling and bundle selling, and examine how the optimal pricing and rose design in each setting impacts user behavior and app performance. In a natural model of dating app operation, we compare how different rose policies impact platform revenue, as well as aggregate user surplus and total social welfare.

1.1. Contributions

The main contributions of our work are four-fold:

1. We present a simple, natural model for the operation of a dating app that designs and prices roses (cf. Section 2). In our model, users are forward-looking and engage in costly search on the dating app over two periods. In each period, they see a candidate match and decide whether to swipe left, swipe right, or swipe right and purchase/send a rose to maximize their chance of matching. Based on the user's decision, they have a chance to match with the candidate and depart from the platform stochastically. In this model, we investigate selling strategies which can offer menus of rose options, and focus specifically on two special cases: separate selling, where roses are offered individually, and bundle selling, where roses can only be purchased as a bundle.

2. Under all selling strategies considered, we characterize the optimal user behavior, and then solve for the revenue-maximizing pricing and design of roses (cf. Theorems 1 and 3). We find in both the separate selling and bundle selling cases that the revenue-maximizing rose design is such that users can only match by purchasing a rose (cf. Theorems 2 and 3). When offering the optimally designed roses, we find that the revenue-maximizing prices under both separating selling and bundle selling are non-monotonic with the search cost, and investigate when the platform can increase the price even as the search cost increases (cf. Theorems 1 and 3).
3. We next compare the outcomes of separate selling versus bundle selling under the revenue-maximizing choices of rose price and design. We find that separate selling of roses always leads to superior revenue (cf. Theorem 5). For users, we find that their aggregate expected surplus is also higher under separate selling (cf. Theorem 6).
4. Finally, we compare separate selling and bundle selling against the full, mixed bundling case where the app can offer both individual roses and rose bundles. We find numerically that separate selling achieves nearly all the performance of mixed bundling policy with respect to both revenue and social welfare (cf. Section 4.3).

Taken together, our work gives the first formal analysis of rose-like products for use in online dating. We find that, when appropriately optimized, roses can not only enhance app revenue but also increase user welfare and facilitate more effective matching. For practitioners, our work motivates the use of rose-like products and yields guidelines for how to implement them (namely to make them as effective as possible) and price them based on simple parameters of the market.

1.2. Literature Review

The literature on matching markets and their applications to online dating platforms is large and multi-disciplinary. Here, we highlight several streams of papers compare and contrast them with our work.

Monetization with Strategic Customers and Costly Search. The body of work most closely related to our study considers various aspects of how to monetize markets where strategic customers engage in costly search, as they do in online dating. For instance, Cui and Hamilton (2022) consider a natural model of dating app monetization where customer valuation decays over time due to fatigue, and use it to evaluate how subscription length affects both profit and steady-state user base size. Wang and Sahin (2018) study user choice under costly search using a consider-then-choose model and analyze how consumer search costs affect retailers' assortment and pricing strategies. Some other related work that focuses on dynamic pricing incudes Talluri and Van Ryzin (2004), who study dynamic pricing and assortment under a discrete choice model, and Ulu et al. (2012) explore how does a firm modifies its product over time when learning about consumer tastes. Hopp and Xu (2005) and Aksoy-Pierson et al. (2013) investigate the optimal product design and pricing in competitive markets.

Bundling is one of the main monetization strategies in the literature. Rios and Torrico (2023) investigate content bundling on social media platform. Roels et al. (2023a) shows how bundling can be beneficial in a duopoly competition,(de Cornière and Sarvary 2023) study bundling selling in online auctions (Huang et al. 2022) explore competitive bundling strategy for digital service firms. Wu et al. (2022) investigate the interplay between product bundling and customer search and its implications for a monopolist's optimal pricing strategy. Roels et al. (2023b) explore how does digital service firms design and bundle their offering to capture a large market while seeking differentiation from competition. Sun et al. (2025) explore the selection and pricing of a single bundle from a range of products.

Coordinating Matches on Platforms While we consider roses primary through the lens of revenue-maximization, roses can also be understood as a *signaling* mechanism, which allows user to indicate the intensity of their interest. Previous work has emphasized the necessity of signaling to reduce congestion and facilitate efficient matching, for instance Arnosti et al. (2021) and Brubach et al. (2021) explore how platform congestion and contention affect match quality, while Aouad and Saritaç (2020) model real-time decision making in high-speed, time-constrained environments. In online dating, Aouad and Saban (2023) and Rios and Torrico (2023) directly propose mechanisms to coordinate offer sets of men and women and improve match outcomes. Wu et al. (2018) further consider a matchmaking market with network effects and strategic consumers, highlighting how user behavior shapes matching efficiency. Wu (2015) investigates the key mechanisms behind successful matches in advertising networks. More generally, Bimpikis et al. (2024) explore the value of information disclosure on the supply side to incentivize engagement, while Besbes et al. (2023) analyze signaling competition in two-sided markets and show how strategic signaling affects equilibrium outcomes. Our work is complementary to this literature as it emphasizes the effectiveness of roses as a monetization tool as well.

Empirical Analysis of Online Recommendation/Matching Markets There is a large body of work empirically analyzing various aspects of the matching platforms, such as popularity bias (Celdir et al. 2024), user privacy (He et al. 2025), information asymmetry (Shi and Viswanathan 2023), and user search behavior (Fong 2024), all of which inform our modeling choices. Most directly relevant to our work is Lee and Niederle (2015) who provide experimental evidence that sending a virtual rose in online dating markets significantly increases the likelihood of matching. Other relevant papers include Bojd and Yoganarasimhan (2021) who examine the effect of user's popularity information on his or her demand in a mobile dating platform. They show that displaying popularity information can increase a candidate's attractiveness to users, but excessive popularity information may backfire since users are more likely to have rejection concerns. Shen et al. (2024) analyze large-scale data from an online dating site to demonstrate how preference mismatches are common, and how information provision can correct for these inefficiencies. Motivated this empirical work, our paper investigate how users benefit from paid visibility improvement products like roses, and builds off by theoretically analyzing how platforms should design rose to increase revenue.

1.3. Paper Outline

The remainder of the paper is as follows. In Section 2, we set our notation and describe the mechanics of our model. In Section 3, we consider the special cases where the platform separately sells roses in each period and where the platform only offers a bundle of roses in the first period. In Section 4, we then compare and contrast the optimal separate selling and bundle selling policies, as well as numerically compare them with the fully optimal rose policy. Finally in Section 6, we conclude and highlight avenues for future work.

2. Model and Preliminaries

We consider an online dating platform that serves a market of users over two periods. In each period $i \in \{1, 2\}$, the user sees a candidate with attractiveness a_i, which is drawn independently from a (known) uniform attractiveness distribution Uni$[0, 1]$. We suppose each user has a valuation function which maps the attractiveness of a candidate to their willingness-to-pay for a match, $v(a) := \frac{a}{1-a}$. Based on the candidate's attractiveness, the user can decide to incur search cost $c \in [0, 1)$ to pursue interest in matching (for instance by composing a message). If the user pursues the candidate, they have a probability of matching with a candidate, $q(a)$, that depends on the candidate's own attractiveness as well as the likelihood they are reciprocally shown to the candidate. Specifically, we suppose that $q(a) := \Pr(\text{Matching}) = \Pr(\text{Matching} \mid \text{Seen}) \Pr(\text{Seen}) = \frac{1-a}{1+\delta}$, where $1 - a$ the probability of matching if seen by the candidate, and $\frac{1}{1+\delta}$ is baseline probability of being seen by/shown to the candidate for some platform specific parameter $\delta \geq 0$.

To increase the probability of matching with specific candidates, the platform offers users digital *roses* for purchase. Roses are offered either separately at a price p_r, or as a bundle of two roses at price p_b, where WLOG we suppose $0 \leq p_r \leq p_b$. If a user decides to purchase and use a rose for a specific candidate, then they are always shown to that candidate which boosts their probability of matching by a factor of $1 + \delta$. Thus, sending a rose to a candidate with attractiveness a increases the matching probability to $q(a|r) := \Pr(\text{Matching}|\text{Rose}) = 1 - a$. If a user matches with the candidate, we suppose they leave the platform. For a depiction of the platform-user dynamics, see Fig. 2.

At the beginning of each period, users see a candidate match and then strategically choose one of four options:

1. A user can purchase an individual rose for a price p_r to send to the candidate match in this period (r), expending effort c.
2. A user can purchase a bundle of two roses (b) for a price p_b. Such a user will always send one rose to the candidate match in this period expending effort c, and will save the second rose for potential future use.
3. A user can swipe right on the candidate match but not purchase a rose (s), indicating their interest in the candidate and expending effort c.
4. A user can swipe left on the candidate (n), indicating their disinterest and progressing to the next period with no further actions.

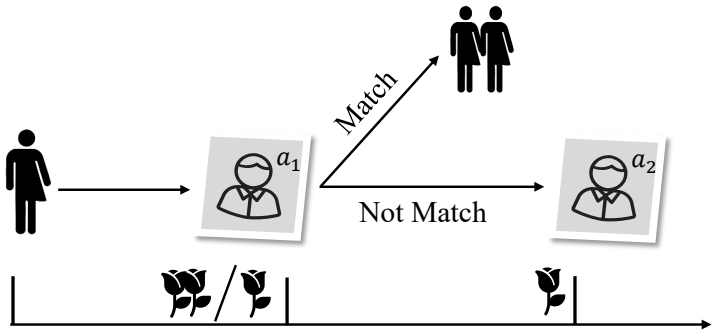


Figure 2 **Dating app model when the platform offers both bundled roses and single roses.** In the first period, users see a candidate and may choose to buy the bundle, send a rose, swipe right, or swipe left. Depending on their action, they either match with the candidate and leave the platform, or return for the second period. In the second period, users can choose to send a rose, swipe right, or swipe left.

We suppose users are rational, forward-looking, and choose the option that maximizes their total expected utility across two periods. That is, when making a purchasing decisions in the first period, user's consider the sum utility-to-go in the first period and the expected utility to go in the second period based on their initial option. Suppose the platform follows a mixed strategy (MS) of offering roses individually a price p_r and as a bundle (of two roses) at price p_b. Then, the total utility of a user in the first period who observes a candidate with attractive a_1 under the four options (r, b, s, and n) is:

$$u_1^{MS} = \begin{cases} u_{r,1}^{MS} := (1+\delta)q(a_1)v(a_1) - c + (1-(1+\delta)q(a_1))\mathbb{E}[u_2^{MS}] - p_r & \text{if they decide to buy a single rose} \\ u_{b,1}^{MS} := (1+\delta)q(a_1)v(a_1) - c + (1-(1+\delta)q(a_1))\,\mathbb{E}[u_2^{MS}] - p_b & \text{if they decide to buy the bundle} \\ u_{s,1}^{MS} := q(a_1)v(a_1) - c + (1-q(a_1))\mathbb{E}[u_2^{MS}] & \text{if they decide to swipe right} \\ u_{n,1}^{MS} := \mathbb{E}[u_2^{MS}] & \text{if they decide to swipe left} \end{cases}$$

where $\mathbb{E}[u_2^{MS}]$ refers to the expected utility of users in the second-period, and the superscript MS denotes the scenario that the platform offer a mixed selling of single rose and bundled roses.

We are interested in understanding the platform's total revenue across two periods as a function of the prices p_r and p_b, which we denote by $\mathcal{R}^{MS}(p_r, p_b)$. When referring to the optimal policies we will drop the dependence on the price, i.e., $\mathcal{R}^{MS} := \max_{p_r,p_b} \mathcal{R}^{MS}(p_r, p_b)$. Formally,

$$\begin{aligned} \mathcal{R}^{MS}(p_r, p_b) =& p_b \Pr(\text{Buy the bundle in period 1}) + p_r \Pr(\text{Buy a rose in period 1}) \\ &+ p_r \Pr(\text{Do not match in period 1, buy a rose in period 2}) \end{aligned} \tag{1}$$

where in the above, a user can only buy the bundle the first period as there are two periods and $p_r \leq p_b$.

Under a mixed pricing strategy, the analysis is complicated to a degree by the interaction (and cannibalization) between single and bundled roses. Often, it will be convenient to examine the special cases where either only single roses are offered ($p_b = \infty$) or only a bundle of roses is offered. When the bundle of roses is removed, we will refer to the strategy as separate selling and denote the revenue by $\mathcal{R}^{SS}(p_r) :=$

$\mathcal{R}^{MS}(p_r, \infty)$. When the single rose option is removed and supposing the customers can only purchase the bundle in the first period, we will refer to the strategy as bundle selling and denote the revenue by $\mathcal{R}^{BS}(p_b) := p_b \Pr(\text{Buy the bundle in period 1})$. In the remainder of this section we will discuss the above model and it's motivation.

2.1. Model Discussion

discussion of attractiveness as a single number that partially relative and partially common. Explain Carr (2016). Attractiveness is relative (Hamilton (2024) for evidence)

In our model, we assume that users have a personal valuation $v(a) = \frac{a}{1-a}$ for a candidate with the attractiveness a. This functional form satisfies many behavioral characteristics that are both intuitive and observed in practice. For example, $v(a)$ is monotone increasing in a, which means the more attractive a candidate is to the user the higher the user's valuation. When the attractiveness is zero, the valuation is also zero, which means that there is no value in the eyes of the user for a candidate that has zero attractiveness for them. We also assumed a maximum level of $a = 1$ where it will result in a valuation of infinity for the user. **[robustness], potentially mention odds function Zhang and Maloney (2012)**

We also assumed the basic matching probability of users when they see the candidate with attractiveness a is $q(a) = \frac{1-a}{1+\delta}$, which is decreasing in a. This is natural as, while attraction has relative component, dating app users are also delineated by their broad appeal, for instance on Tinder users have internal ELO-type score which maps to their general attractiveness (Carr 2016). More attractive candidates receive a higher volume of likes/swipes which can compete with a users matching request resulting in a lower probability reciprocal matching.

Attractiveness and it's effect on matching has been studied empirically in Fisman et al. (2006), Bruch and Newman (2018), Asendorpf et al. (2011), Hitsch et al. (2010) where in each paper authors focus on different attributes of attractiveness of users such age, education, and religion impact the matching process. In our model, we do not study the different factors and contribute to a user's attractiveness, instead we aggregate all of these factors in a singular value a (again, note that leading dating apps similarly keep an internal ELO score for users (Carr 2016)). One way to think of a is as the difference between the attractiveness of a candidate from the user's perspective and the user's own self-perceived attractiveness. The reason we assume that the value of attractiveness a is the relative attractiveness premium for the candidate if they are matched with the user, is that a rational candidate will only try to match with someone who they deem more attractive than a fixed base value.

By sending a rose, we assume that the user will be pushed forward in the request queue (see Fig. EC.4). The effectiveness of this boosting in the position of the user can range from zero to ∞ ($\delta \geq 0$). When $\delta = 0$ it means that sending a rose will not provide any advantage with respect to other competitors, for instance when a candidate can easily observe of their match requests (although often these are hidden). On the other

hand when $\delta = \infty$ the probability of match will simply be the probability of match if shown, in another word by not sending the rose the probability of match will be even lower than what it could actually been due to the queue effect. So, as δ increases and approaches ∞ it means that not sending a rose to candidate leaves the user with zero chances of match because they will never be shown by the platform (they will end up on the end of the request queue).

In our model, we assume that the positive process of engaging with a candidate (i.e., swiping right or sending a rose) incurs a per-period search cost of $c > 0$. Each user will wait until they acquire the result of a match request. We incorporate this assumption as a search cost value c, reflecting the time value associated with waiting for a match. This cost c is incurred by the user per request sent, regardless of whether a rose is send or not. This search cost c is constant for all periods.

Online dating is a multi-period dynamic process where users initiate matches in each period. If a match is made, they leave the platform; otherwise, they will return to the platform again. We assume users are strategic and thus they will consider the total utilities to go when they make decisions about requesting a date and buying roses (Cachon and Swinney 2009, Aflaki et al. 2020). Since consumers' strategic behavior would need to account for utility across all future periods which increases complexity and makes the model computationally intensive, we consider a two-period framework to simplify the analysis while still capturing the essential dynamics of online dating process and consumers' strategic behavior. These models are common in this line of literature. For example, Wu et al. (2018), Rios and Torrico (2023) and Basu et al. (2024) use two period models to study the user's interaction with the platform.

3. Separate and Bundle Selling

In Section 2, we presented a model where the seller offers a menu of roses, either individually at price p_r or as a bundle of two roses at price p_b. However, characterizing the the optimal prices in this setting is challenging. Instead, in section we will restrict our attention to two special cases: *separate selling* where the platform offers only a single rose for sale (denoted by the superscript SS), and *bundle selling* where the platform offers only a bundled rose for sale (denoted by the superscript BS). In each case, we will explicitly characterize the utility-maximizing customer behavior and derive the revenue-maximizing specification of price and rose effectiveness.

We note that in practice, platforms typically offer a wide range of rose bundle options, with some emphasizing the individual rose by setting high prices for powerful one-time use match-enhancers (see Hinge in Fig. 1) whereas other platforms emphasize bundles of roses like products by offering weakening the product and offering strong quantity based discounts (see Bumble and Tinder in Fig. 1). Restricting our analysis to the extremes of separate selling and bundling allows us to understand the value of roses across these two regimes and weigh-in on what drives their effectiveness. Further, such an approach is common in the economic bundling literature where restriction to special cases of two items (Bhargava 2013, Hart and

Nisan 2017) is common, as are comparison between separate selling and bundling selling (see for instance Hartline and Roughgarden (2009), Abdallah et al. (2021) for analysis of separate selling vs. grand bundle selling in various contexts). Finally, as we will see in Section 4.3, the best of these two special cases will nearly approximate the mixed bundle setting in our model.

3.1. Optimal Separate Selling

In separate selling (SS), after seeing the first candidate the user choices between three options. The expected utility-to-go across the two periods for the three decision scenarios are: (i) purchasing and using a single rose $u^{SS}_{r,1}$, (ii) swiping right without purchasing the rose $u^{SS}_{s,1}$, and (iii) neither purchasing nor swiping right $u^{SS}_{n,1}$. Each are derived as follows:

$$
\begin{aligned}
u^{SS}_{r,1}(a_1) &= (1+\delta)q(a_1)v(a_1) - c - p_r + (1-(1+\delta)q(a_1))\mathbb{E}[u^{SS}_2],\\
u^{SS}_{s,1}(a_1) &= q(a_1)v(a_1) - c + (1-q(a_1))\mathbb{E}[u^{SS}_2],\\
u^{SS}_{n,1}(a_1) &= \mathbb{E}[u^{SS}_2],
\end{aligned}
$$

where $\mathbb{E}[u^{SS}_2]$ denotes the user's optimal expected second-period utility in separate selling. In the second period, a user engages with a candidate if the utility for doing so is positive, i.e., if $u^{SS}_{s,2}(a_2) = \frac{a_2}{1+\delta} - c \geq 0$, where the double subscript denotes the second period. The user instead purchases a rose if it maximizes their utility, i.e., $u^{SS}_{r,2}(a_2) = a_2 - c - p_r \geq (u^{SS}_{s,2}(a_2))^+$, where $(x)^+$ denotes $\max\{x, 0\}$. Therefore, a user earns the expected second-period utility of:

$$
\begin{aligned}
\mathbb{E}[u^{SS}_2] &= \mathbb{E}[u^{SS}_{r,2}(a_2)|\text{Buy Rose}]\Pr(\text{Buy Rose}) + \mathbb{E}[u^{SS}_{s,2}(a)|\text{Swipe Right}]\Pr(\text{Swipe Right}) + \mathbb{E}[u^{SS}_{s,2}(a)|\text{Swipe Left}]\Pr(\text{Swipe Left})\\
&= \left(\frac{1+\max\{\frac{p_r(1+\delta)}{\delta}, c+p_r\}}{2} - c - p_r\right)\left(1 - \max\{\frac{p_r(1+\delta)}{\delta}, c+p_r\}\right)^+ + \left(\frac{c+\frac{p_r}{\delta}}{2} - c\right)\left(\frac{p_r(1+\delta)}{\delta} - c(1+\delta)\right)^+.
\end{aligned}
$$

where the utility from swiping left is zero. In this case, the platform's total revenue across the two periods will be:

$$
\mathcal{R}^{SS}(p_r) = p_r \Pr(\text{Buy a rose in period 1}) + p_r \Pr(\text{No match in period 1 and buy a rose in period 2}). \quad (2)
$$

Now, we are ready to characterize user behavior under separate selling. Since users are forward-looking, they must balance a trade-off between whether to pursue the first candidate vs. waiting and seeing another candidate in the second period. This trade-off manifests in our model as three distinct regimes depending on the attractiveness of the first candidate. If that candidate is not attractive the user will swipe left, if they are somewhat attractive the user will swipe right but not send a rose (hedging between this candidate a candidate in the next period), otherwise if the candidate is very attractive they will send a rose. We characterize these distinct levels of attractiveness in the following lemma.

Lemma 1 (Separate Selling User Behavior). *In the first period, there exists unique thresholds,*

$$a_{r,1} = \frac{p_r(1+\delta) + \delta\mathbb{E}[u_2^{SS}]}{\delta(1+\mathbb{E}[u_2^{SS}])},\ a_{n,1} = \frac{c(1+\delta) + \mathbb{E}[u_2^{SS}]}{1+\mathbb{E}[u_2^{SS}]},\ \text{and } a_{rn,1} = \frac{c+p_r+\mathbb{E}[u_2^{SS}]}{1+\mathbb{E}[u_2^{SS}]},$$

such that:

(i) If $p_r < \min\{\delta c, 1-c\}$, users swipe left if $a_1 < a_{rn,1}$ and they purchase a rose if $a_1 \geq a_{rn,1}$.

(ii) If $p_r \in \left[\delta c, \frac{\delta}{1+\delta}\right]$, users swipe left if $a \leq a_{n,1}$, swipe right without purchasing a rose if $a \in [a_{n,1}, a_{r,1})$, and purchase a rose if $a \geq a_{r,1}$.

(iii) If $p_r > \min\{\frac{\delta}{1+\delta}, 1-c\}$, no one buy roses.

Lemma 1 describes user behavior in the first period based on the attractiveness of the candidate shown to the user. We note that we can also deduce the user behavior in the second period from Lemma 1 by replacing $\mathbb{E}[u_2^{SS}]$ with zero, since we only consider two periods and thus in the second period there is no expected utility in the next period. That is, in the second period the thresholds are:

$$a_{r,2} = \frac{p_r(1+\delta)}{\delta},\ a_{n,2} = c(1+\delta),\ a_{rn,2} = c+p_r.$$

From Lemma 1, we also can understand how users behave in the first period as a function of the rose price, p_r. We note that when p_r is relatively small ($p_r < \min\{\delta c, 1-c\}$), users will not swipe right and instead only send roses or abstain in the first period. However when p_r is larger, user behavior is enriched to include the prospect of swiping right but not purchasing. This dual behavior based on the value of p_r complicates the firms optimization of this price. However, in spite of the two cases, it turns out that the resulting two period revenue function is in fact concave in p_r and has a unique maximizing price.

To study the concavity of the revenue function we break the revenue function into two pieces, let $\mathcal{R}_l^{SS}(p_r)$ and $\mathcal{R}_g^{SS}(p_r)$ be the revenue functions when $p_r < \min\{\delta c, 1-c\}$ and $p_r \in \left[\delta c, \frac{\delta}{1+\delta}\right]$, respectively.

Lemma 2 (Separate Selling Revenue Concavity). *$\mathcal{R}_l^{SS}(p_r)$ and $\mathcal{R}_g^{SS}(p_r)$ are strictly concave in p_r. Furthermore, $\mathcal{R}^{SS}(p_r)$ is strictly concave in p_r.*

Given Lemma 2, it follows that there is a unique optimal price p_r^* and we can study how this optimal price changes as the parameters of the problem vary. Specifically, in Theorem 1 we characterize the optimal p_r^* and explain how it varies as the advantage of sending a rose (measured by δ) increases.

Theorem 1 (Separate Selling Price Dynamics).

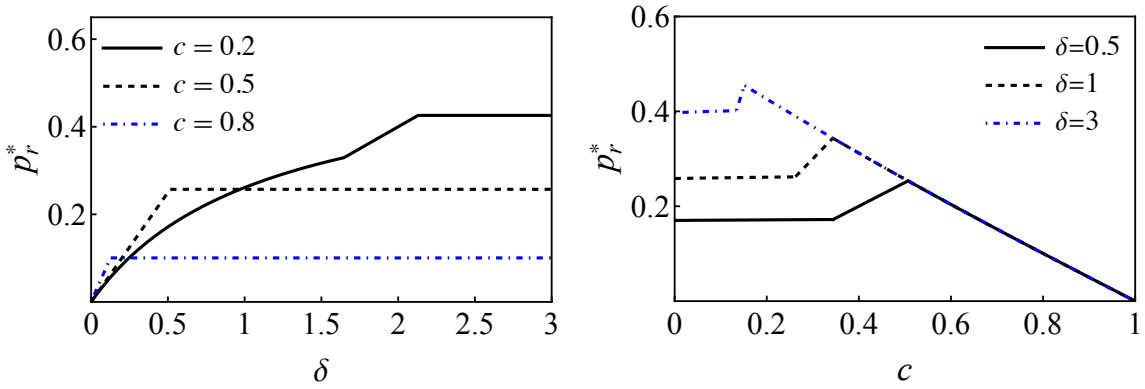
(i) There exist thresholds $\underline{c}(\delta)$ and $\overline{c}(\delta)$, such that

$$p_r^* = \begin{cases} p_{rg}^* & \text{if } c \leq \underline{c}(\delta), \\ \delta c & \text{if } \underline{c}(\delta) < c \leq \overline{c}(\delta), \\ p_{rl}^* & \text{if } \overline{c}(\delta) < c, \end{cases}$$

where p_{rl}^* and p_{rg}^* are the unique maximizers of $\mathcal{R}_l^{SS}(p_r)$ and $\mathcal{R}_g^{SS}(p_r)$.

(ii) The revenue-maximizing price p_r^* is unimodal with respect to the search cost c: it increases first and then decreases.

Theorem 1 implies that when the search cost c is low, the optimal price of the rose is chosen so that users exhibit three behaviors (swipe left, swipe right, or buy and send a rose). However, when the platform ecosystem is such that user search cost is high, then the roses will be priced in a way that convince the users to always either swipe left or send a rose but never just swipe right. Thus, in cases of high search cost, the platform is reduced to one where users pay-per-message to interact with candidate matches. Moreover, note the value of c which is high enough to induce no swipe right behavior depends on δ. When δ is extremely large (i.e. the rose is highly effective) then the value of a right swipe is low, thus in this situation, the user will never choose to swipe right. For a graphical depiction of this price behavior see Fig. 3.



(a) p_r^* varies with δ (b) p_r^* varies with c

Figure 3 **p_r^* as δ and c vary.** Depicted are plots showing how the revenue-maximizing p_r^* varies with δ and c. On the left, p_r^* increases with δ and approaches a constant as δ becomes larger. On the right, p_r^* first decreases, then increases, and finally decreases with, tending to zero as c approaches 1.

From Theorem 1 and Fig. 3, we can see that there is a complicated interaction between p_r and δ. Further, we note that in many instances, a platform sets both the price and effectiveness of the rose and thus can control both p_r and δ simultaneously. In our final result of this section, we will characterize the revenue maximizing joint specification of δ and p_r.

Theorem 2 (Optimal Joint Separate Selling Rose Design).

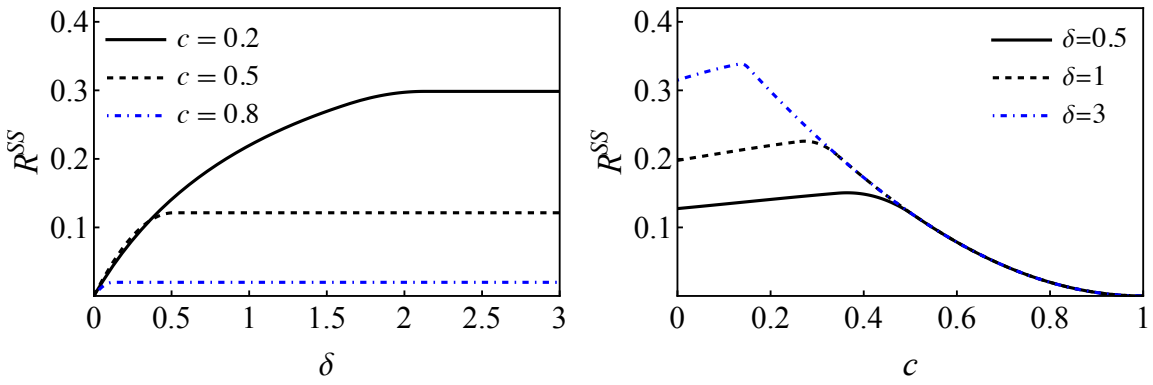
(i) The maximum revenue, $\mathcal{R}^{SS}$, is an increasing function of δ.

(ii) The maximum revenue, $\mathcal{R}^{SS}$, is a unimodal function of c, and the revenue is maximized at some c^*.

In Theorem 2, we find the revenue is maximized under rose designs which make δ as large as possible, and where search is not necessarily frictionless for users. The first part of this theorem is intuitive, increasing δ increases the value proposition of a rose by increasing the matching probability resulting in an increase

in the revenue. The fact that the revenue does not decrease as search cost increases is less intuitive. Higher search cost reduces a users willingness to interact with the platform and thus ostensibly lowers second stage participation and thus revenue. However, a moderate level of search friction will shift users away from low commitment actions (swiping right) and toward higher intent action (sending a rose) which increases the ability of the platform to extract revenue. It is only when search cost become sufficiently large then that the overall engagement declines enough to offset the above effect, producing a unimodal relationship identified in Theorem 2.

In practice, this result highlights that the platform should not necessarily seek to eliminate search frictions, and instead may profit from platform designs with moderate levels of friction which enhance monetization efforts by increasing the value of paid features such as roses. On the other hand, the platform should try to maximize the effectiveness of the roses, δ, by guaranteeing visibility for example, placing those who sent a rose at the top of the queue.



(a) Optimal revenue varies with δ

(b) Optimal revenue varies with c

Figure 4 $\mathcal{R}^{SS}$ **as** c **and** δ **vary.** Depicted are plots showing how the optimal revenue $\mathcal{R}^{SS}$ varies with δ and c. On the left, $\mathcal{R}^{SS}$ increases with δ and approaches a constant as δ becomes larger and larger for all levels of c. On the right, $\mathcal{R}^{SS}$ first increases and then decreases with c for all levels of δ.

In Fig. 4, we visualize this behavior in our model. We note that the location of the revenue-maximizing search cost shifts leftward as δ increases. This pattern reflects the interaction between search friction and visibility. When δ is small, roses only weakly improve matching outcomes, so users require relatively higher search cost before they are willing to switch from swiping right to sending a rose. As δ increases, roses will become more effective, amplifying user's willingness to pay even when the search costs are relatively low. From a design perspective, this interaction implies that platforms who offer more effective roses should attempt to avoid excessive search frictions and conversely when the rose is weak, the platform should rely more on search friction to stimulate demand.

Our finding implies that, in the absence of concerns such as user churn, a platform benefits from making the roses maximally effective. As such, in the remainder of this paper we will use $\delta = \infty$ as a conceptual benchmark for later comparison with bundling and mixed strategies. We study bundle rose policies next.

3.2. Optimal Bundle Selling

In this subsection, we will characterize the optimal user behavior and revenue-maximizing pricing and design when the platform offers a bundle of roses. To begin, in bundle selling (BS) the total utilities across both periods for three decision scenarios are: purchasing the bundle $u_{b,1}^{BS}$, swiping right without purchasing the bundle $u_{s,1}^{BS}$, and neither purchasing nor swiping right $u_{n,1}^{BS}$. Formally, we express these as:

$$
\begin{aligned}
u_{b,1}^{BS}(a_1) &= (1+\delta)q(a_1)v(a_1) - c - p_b + (1-(1+\delta)q(a_1))\,\mathbb{E}[u_{b,2}^{BS}],\\
u_{s,1}^{BS}(a_1) &= q(a_1)v(a_1) - c + (1-q(a_1))\,\mathbb{E}[u_{s,2}^{BS}],\\
u_{n,1}^{BS}(a_1) &= \mathbb{E}[u_{s,2}^{BS}],
\end{aligned}
$$

where $\mathbb{E}[u_{b,2}^{BS}]$ and $\mathbb{E}[u_{s,2}^{BS}]$ denote the user's expected second-period utility under bundle selling when users either purchased the bundle in the first period and did not purchase the bundle in the first period, respectively. If users purchased the bundle in the first period and used the rose, their utility is:

$$
\mathbb{E}[u_{b,2}^{BS}] = \mathbb{E}_{a_2\sim F}\left[((1+\delta)q(a_2)v(a_2) - c)^+\right] = \int_c^1 (a_2 - c)da_2 = \frac{(1-c)^2}{2}.
$$

If users did not purchase the bundle in the first period but choose to swipe right, then:

$$
\mathbb{E}[u_{s,2}^{BS}] = \mathbb{E}_{a_2\sim F}\left[(q(a_2)v(a_2) - c)^+\right] = \begin{cases} \frac{(1-(1+\delta)c)^2}{2(1+\delta)} & \text{if } c < \frac{1}{1+\delta},\\ 0 & \text{if } \frac{1}{1+\delta} \le c < 1. \end{cases}
$$

In this case, the bundling revenue function can be formulated as:

$$
\mathcal{R}^{BS}(p_b) = p_b \Pr(\text{Buy the bundle in period 1}) \tag{3}
$$

As in the separate selling case, before conducting the full analysis in the bundling case, we first give a threshold characterization of user behavior based on the initial candidate's attractiveness.

Lemma 3 (Bundle Selling User Behavior). *There exists a unique threshold a_b such that users will buy the bundle if and only if $a_1 \ge a_b$, where*

$$
a_b = \begin{cases} \max\{\frac{\delta(1-c(1+\delta))^2+2p_b(1+\delta)^2}{\delta(1+(1+\delta)(3-2c))}, \frac{1+c^2(1+\delta)^2+2p_b(1+\delta)}{(1+\delta)(3+c^2-2c)}\} & \text{if } c < \frac{1}{1+\delta},\\ \frac{2(c+p_b)}{3+c^2-2c} & \text{if } \frac{1}{1+\delta} \le c < 1. \end{cases}
$$

Lemma 3 implies that the user's decision to buy a bundle or not depends only on the attractiveness of the first candidate displayed by platform and the relation between the price of the bundle and its boosting effect. Next, using the bundling revenue function formulated in Eq. (3), we prove that the optimal bundle price is well-behaved.

Lemma 4 (Uniqueness of Optimal Bundle Price). *Revenue function $\mathcal{R}^{BS}(p_b)$ is concave in p_b.*

in Lemma 4 we show that the bundling revenue is concave in p_b and thus the optimal price is unique. This concavity is not trivial because the revenue is tied to both periods, and the threshold we established in Lemma 3. By guaranteeing the uniqueness of the optimal bundle price in Lemma 4 we have the mathematical foundation to compute the closed form price characterization in Theorem 3.

Theorem 3 (Bundle Pricing Dynamics). *(i) There exists thresholds $\underline{c}_b(\delta)$ and $\overline{c}_b(\delta)$, such that*

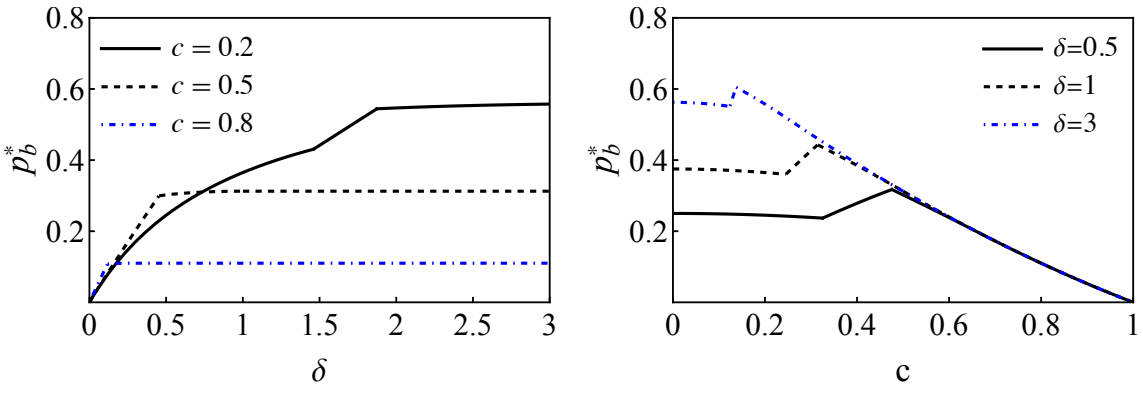
$$p_b^* = \begin{cases} \frac{\delta(3-(1+\delta)c^2)}{4(1+\delta)} & \text{if } c \le \underline{c}_b(\delta), \\ \frac{\delta - c\delta(1+\delta)(c(c(1+\delta)(c\delta+c-2)+3\delta+4)-6(1+\delta))}{2(1+\delta)(3+2\delta-2c(1+\delta)+c^2(1+\delta)^2)} & \text{if } \underline{c}_b(\delta) < c \le \overline{c}_b(\delta), \\ \frac{\delta+(1+\delta)(2(1-c)-\delta c^2)}{4(1+\delta)} & \text{if } \overline{c}_b(\delta) < c \le \frac{1}{1+\delta}, \\ \frac{(1-c)(3-c)}{4} & \text{if } c > \frac{1}{1+\delta}. \end{cases} \tag{4}$$

(ii) The revenue-maximizing price p_b^* is increasing in δ and as $\delta \to \infty$, p_b^* tends to be a constant.

(iii) The revenue maximizing choice of p_b first decreases, then increases, and finally decreases with respect to the search cost c.

Theorem 3 identifies the optimal bundle price across different search cost regimes and, similar to the separate selling case, the result is a piecewise expression influenced by whether the search cost is sufficiently high enough to discourage right-swiping behavior. Further, note from Theorem 3 that the optimal bundle price increases in δ and is unimodal in c, again mirroring the separate selling case.

The results of Theorem 3 are summarized in Fig. 5, in the first part as δ increases optimal bundle price increases monotonically, where the optimal rose design ($\delta \to \infty$) is also increasing in search cost c. In the second graph the optimal price p_b^* is decreasing first, and then increasing and finally decreasing again in c.



(a) p_b^* varies with δ (b) p_b^* varies with c

Figure 5 **Optimal price as c and δ vary.** Depicted are plots showing how the revenue-maximizing p_b^* varies with δ and c. On the left, p_b^* increases with δ and approaches a constant as δ becomes larger. On the right, p_b^* first decreases, then increases, and finally decreases with, tending to zero as c approaches 1.

Finally, we will conclude this section by characterizing the revenue-maximizing pricing and design under bundle selling and show how it varies with search cost c.

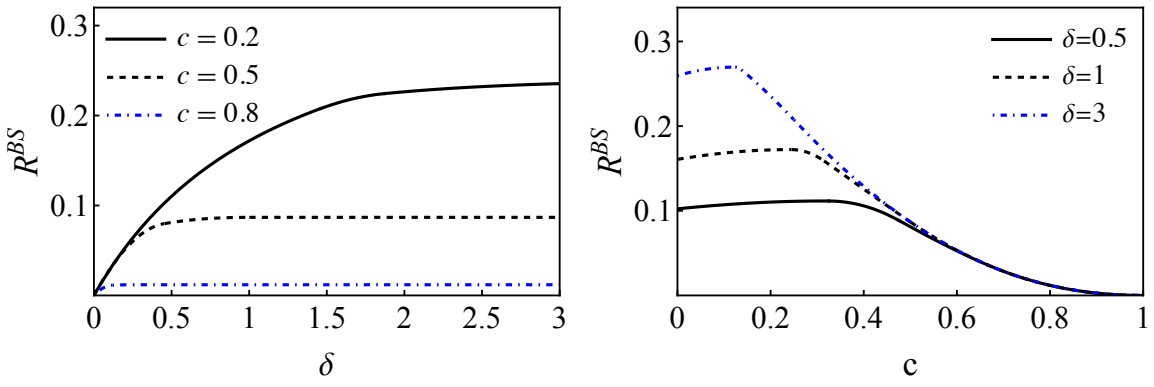
Theorem 4 (Optimal Joint Bundle Selling Pricing and Design). *(i) There exists thresholds* $\underline{c}_b(\delta)$ *and* $\overline{c}_b(\delta)$*, such that*

$$\mathcal{R}^{BS} = \begin{cases} \frac{\delta(3-(1+\delta)c^2)^2}{8(4+3\delta-2c(1+\delta))} & \text{if } c \le \underline{c}_b(\delta), \\ \frac{\delta(1-c(1+\delta))\left(1-c^4(1+\delta)^3+2c^3(1+\delta)^2-c^2(3\delta^2+7\delta+4)+6c(1+\delta)^2\right)}{(3+2\delta-c(1+\delta)(2-c(1+\delta)))^2} & \text{if } \underline{c}_b(\delta) < c \le \overline{c}_b(\delta) \\ \frac{(c^2\delta(1+\delta)+2c(1+\delta)-3\delta-2)^2}{8\left(c^2-2c+3\right)(1+\delta)^2} & \text{if } \overline{c}_b(\delta) < c \le \frac{1}{1+\delta}, \\ \frac{((1-c)(3-c))^2}{8(c^2-2c+3)} & \text{if } c > \frac{1}{1+\delta}. \end{cases} \tag{5}$$

(ii) The optimal revenue $\mathcal{R}^{BS}$ *is increasing in* δ *and as* $\delta \to \infty$,$\mathcal{R}^{BS}$ *tends to be a constant.*

(iii) The optimal revenue $\mathcal{R}^{BS}$ *is unimodal with respect to the search cost c: it increases first and then decreases.*

Theorem 4 demonstrate that, similar to separate selling, revenue is increasing in δ and uni-modal in c. The revenue function can be broken down to four different functions based on the search cost value c compared to our three search cost thresholds $\underline{c}_b(\delta)$, $\overline{c}_b(\delta)$, and $\frac{1}{1+\delta}$. This piecewise nature of the optimal revenue function is a direct result of a piecewise optimal price structure whose own structure was a direct result of customer behavior when facing a different cost structure as illustrated in Theorem 1. We will use these results later on when we compare the properties of all three different selling strategies.



(a) Optimal revenue varies with δ (b) Optimal revenue varies with c

Figure 6 **Optimal revenue as δ and c vary.** Depicted are plots showing how the optimal revenue $\mathcal{R}^{BS}$ varies with δ and c. On the left, $\mathcal{R}^{SS}$ increases with δ. On the right, $\mathcal{R}^{BS}$ first increases and then decreases with c for all levels of δ.

Fig. 6 summarizes the results of Theorem 4, in the first part the optimal revenue $\mathcal{R}^{BS}$ is monotonically increasing in δ where the optimal rose design (i.e $\delta \to \infty$) itself is increasing in search cost c. In the second part we see that the $\mathcal{R}^{BS}$ is uni-model in search cost c and as $c \to 1$ then $\mathcal{R}^{BS} \to 0$.

4. Revenue and Surplus Comparisons

In this section, we compare the optimal performance of the separate selling and bundle selling strategies across three key metrics: the platform's revenue, user surplus, and social welfare. Recall the maximal revenue for both separate selling and bundle selling occurs as $\delta \to \infty$, and as such we will assume δ is made maximal through this section. First we will compare separate selling and bundling selling with one another, then in the final subsection we will compare them with a mixed selling upperbound.

4.1. Revenue Comparisons

In Sections 3.1 and 3.2 we computed closed form optimal revenue expressions for both separate selling and bundle selling. In Theorem 5, we compare these expressions and show that optimized separate selling always generates more revenue than optimized bundle selling.

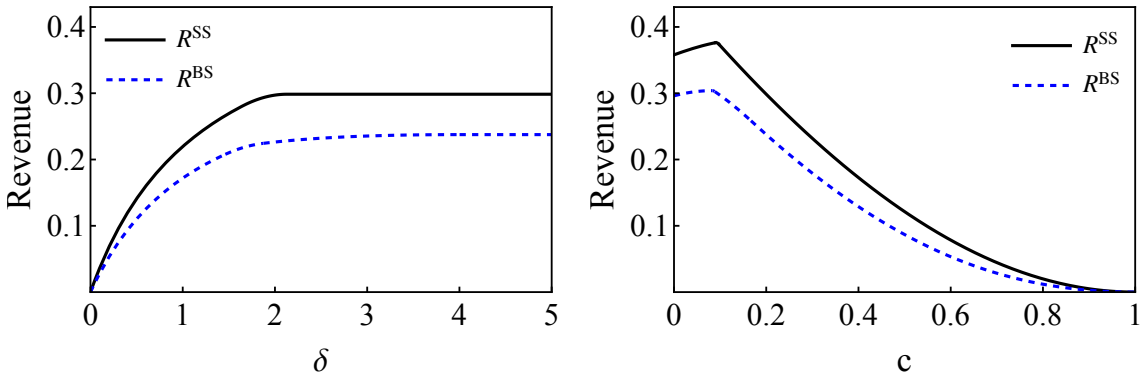
Theorem 5 ($\mathcal{R}^{SS} \geq \mathcal{R}^{BS}$)**.** *When the platform optimizes over both p and δ, separate selling always generates more revenue than the bundle selling.*

Ostensibly, both separate selling and bundling both have distinct advantages. In separate selling, the customer is afforded flexibility to purchase in either period, however this flexibility allows users to purchase, match, and leave before seeing the second period, potentially resulting in lost revenue. Alternatively in bundling selling, the combined nature of the bundle offering decreases volatility in the users valuations allowing for superior price targetting, and there is no loss if users match after buying the roses even if that match occurs in the first period. However, bundle selling deprives users of a second opportunity to purchase. In many classical settings (see Hart and Nisan (2017) for a discussion), the advantages and disadvantages of each strategy lead to distinct regimes where each dominates the other. However, in our setting we find in Theorem 5 is that this superior price targeting is always less valuable than the flexibility to purchase in either period, which in turn implies separate selling revenue-dominates bundle selling. Intuitively, the ability to match between periods creates a type of negative correlation between the two products that stymies the benefits of concentration bundling selling may offer.

We emphasize that this result holds for in the revenue maximizing regime where $\delta \to \infty$. However, we find numerically that this revenue relationship continues to hold for any fixed δ and optimized separate selling and bundle selling prices. In Fig. 7, we compare the revenues as c and δ vary. We note that both selling strategies' revenue (i.e. separate selling and bundle selling) have similar behavior with rose effectiveness δ and search cost c demonstrated in Theorem 2 and Theorem 4. However, the separate selling strategy always results in a higher revenue than bundle selling.

4.2. User Surplus and Social Welfare

Having established the revenue relationship between separate selling and bundle selling, in this subsection we turn our attention to the result user surplus and social welfare under the revenue maximizing policies.



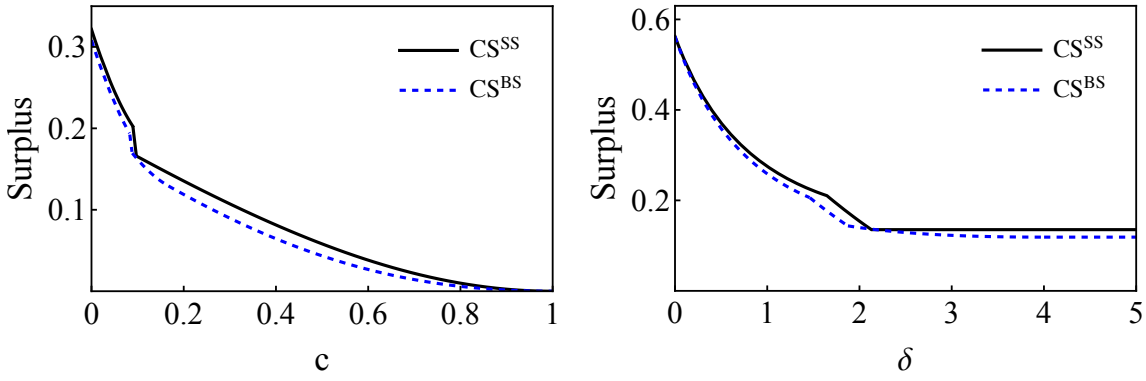
(a) Optimal revenue varies with δ when $c = 0.2$ (b) Optimal revenue varies with c when $\delta = 5$

Figure 7 **Optimal revenue as δ and c vary.** Depicted are plots showing how the optimal revenue $\mathcal{R}_{SS}$ and $\mathcal{R}^{BS}$ varies with δ and c. On the left, both revenue functions increases with δ where the separate selling revenue dominating the bundle selling revenue. On the right, both $\mathcal{R}_{SS}$ and $\mathcal{R}^{BS}$ first increases and then decreases with c for all levels of c where the separate selling revenue dominating the bundle selling revenue.

The social welfare can be expressed as $SW^{SS} = CS^{SS} + \mathcal{R}^{SS}$ and $SW^{BS} = CS^{BS} + \mathcal{R}^{BS}$. In Theorem 6 we study the relationship of both strategies' user surplus and social welfare when the platform sets the prices and parameters at the optimal value.

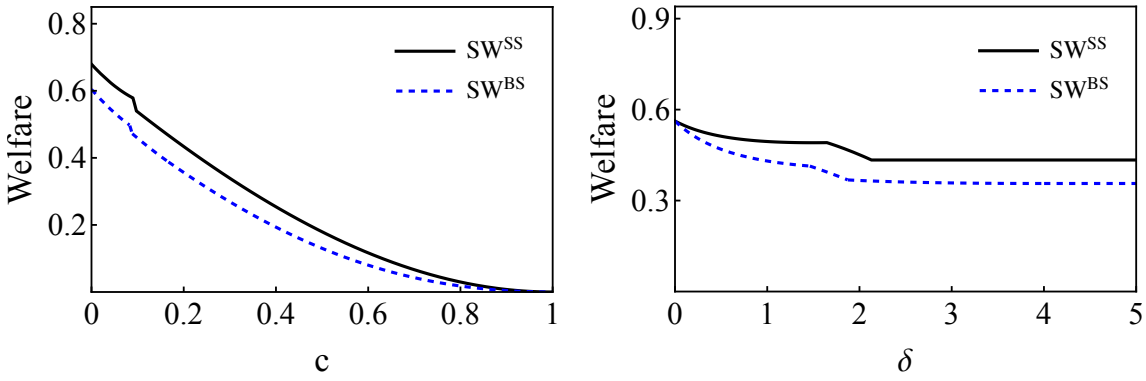
Theorem 6 ($CS^{SS} > CS^{BS}$ **and** $SW^{SS} > SW^{BS}$)**.** *When the platform optimizes over both p and δ, both user surplus and social welfare are higher under separate selling than under bundle selling.*

Similar to Theorem 5, Theorem 6 shows that the separate selling strategy yields higher user surplus and social welfare than the bundle selling strategy when the platform optimizes over both prices and the boosting factor of rose. The flexibility that separate selling offers to the users unlike the bundle selling where they buy an additional rose even if they do not need it necessarily for the next period given the randomness of next candidate attractiveness, makes the user's utility slightly higher under the separate selling compared to the bundle selling strategy. A higher user surplus along side a higher revenue makes the social welfare under the separate selling strategy also higher.Theorem 6 only looks at the optimally designed strategies, we also numerically compare the user surplus and social welfare under separate selling and bundle selling strategies. for any δ and c the user surplus and social welfare under separate selling dominates the bundling selling.



(a) user surplus varies with c with $\delta = 5$ (b) user surplus varies with δ with $c = 0.2$

Figure 8 **User surplus as δ and c vary.** Depicted are plots showing how the user's surplus changes with search cost c or rose effectiveness δ respectively, where separate selling strategy has a slightly higher customer surplus than bundle selling strategy. for both strategies the surplus decreases in c, while it decrease first and stabilizes in δ



(a) Social welfare varies with c with $\delta = 5$ (b) Social welfare varies with δ with $c = 0.2$

Figure 9 **Social welfare as δ and c vary.** Depicted are plots showing the welfare which is the sum of surplus and revenue. the difference between separate selling and bundle selling is more prominent due to a higher revenue from separate selling strategy.

In both Fig. 8 and Fig. 9 we can see that the user's surplus and social welfare is higher in separate selling than bundle selling respectively. In previous section we also showed that the separate selling also generates a higher revenue which makes it a better strategy for both the firm and the users. A higher revenue will also makes the social welfare difference higher that the difference in user's surplus as depicted in the figures.

4.3. Comparison with Mixed Bundle Selling

Regulate the details of the policy in appendix

Finally, having studied both separate selling and bundle selling, in this final subsection we will solve the general mixed bundle selling case where we consider models where the user has the option of buying either

a single rose or a bundle. In this setting the expected utility of a user in the second period depends on their purchasing decision in the first period of whether to buy a bundle. Recall that the original general model we introduce in the beginning was based on the mixed selling strategy where the user has the option to buy a separate rose or a bundle of the roses. The two strategies we studied so far are basically special cases of mixed selling where we could solve theoretically. However, due to complexity of the general model we only will study and compare it with the other two strategies numerically only in the optimal design of the other two strategies i.e. when the rose effectiveness is maximized. Fig. 10 depicts how the optimal revenue, user surplus and social welfare vary with c when $\delta \to \infty$, and we have the following observations.

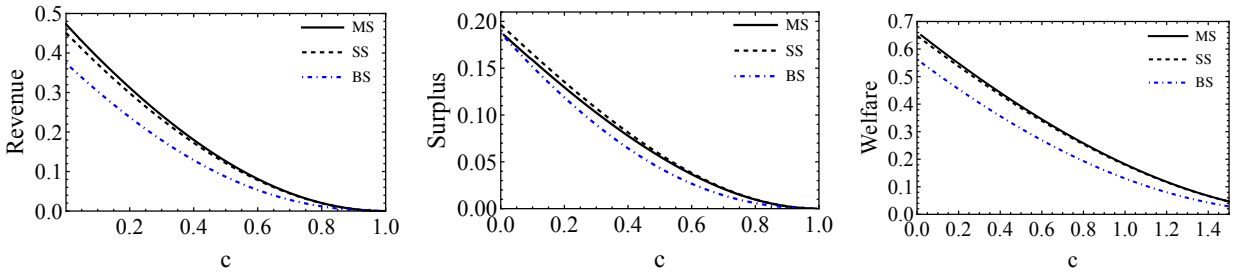
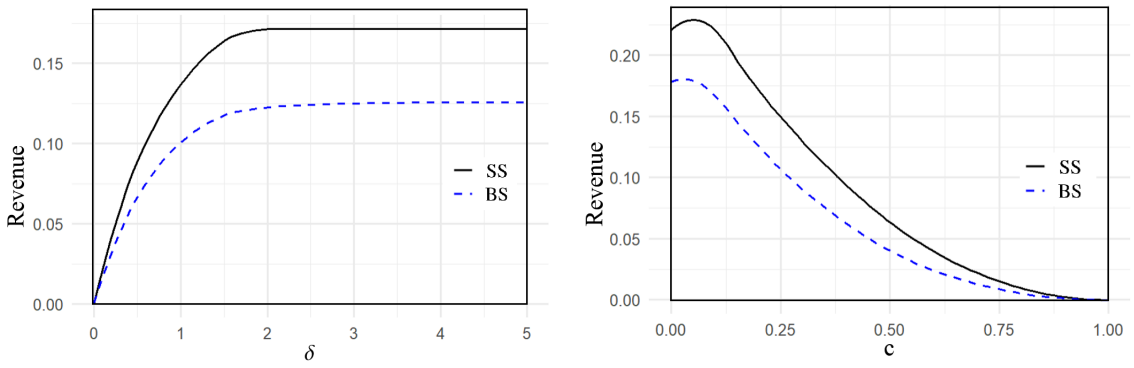


Figure 10 **Revenue, user surplus and social welfare.** The left panel depicts how the optimal revenue varies with c, the middle panel depicts how CS varies with c, the right panel depicts how SW varies with c when $\delta \to \infty$.

For the platform's revenue, the mixed selling strategy obtains the highest revenue when the search cost is not sufficiently high (i.e., $c < 0.95$). The intuition is that when users face choices between purchasing a bundle or a single rose, they tend to buy the bundle upon encountering a high-attractiveness candidate, prefer to purchase a single rose when encountering a low-attractiveness candidate, or choose to swipe left in the first period. However, even in the latter cases, users who remain unmatched in the first period have the motivation to purchase a single rose in the second period. For the platform, compared to a bundle selling strategy, this increases the demand for single roses in the second period; compared to a separate selling strategy, it boosts the demand for the bundled roses. Therefore, the platform can achieve higher revenue under mixed bundling. When the search cost is sufficiently high (i.e., $c > 0.95$), the platform obtains the same revenue under mixed selling and separate selling, both of which are higher than that under bundle selling. The intuition is that excessively high search costs weaken users' incentives to buy bundled roses, as they prefer to secure a match in the first period whenever possible. Thus, users purchase a single rose when they encounter a high-attractiveness candidate and swipe left when they encounter a low-attractiveness candidate. Since this behavior is identical to that observed under separate selling, the platform earns the same revenue under mixed selling as under separate selling.

5. Numerical Extensions

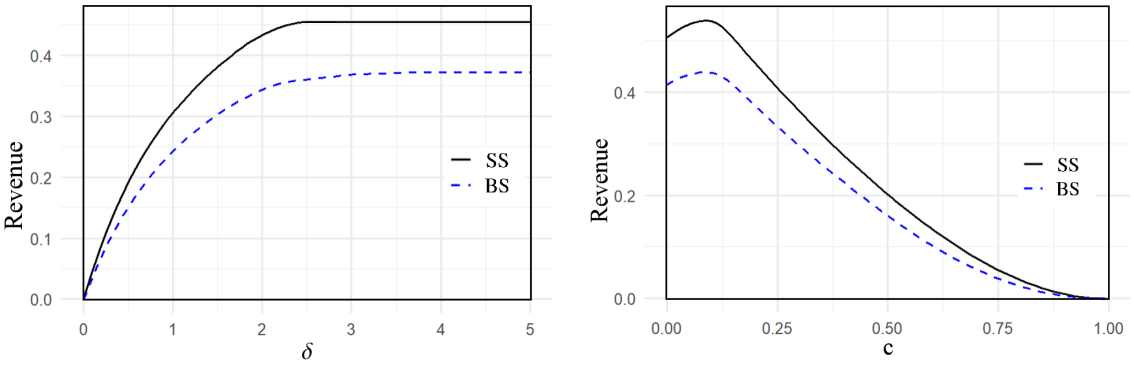
In this section, we try different demand models and different attractiveness distribution to show that our current result (i.e separate selling gives more revenue than bundle selling) is robust. Outside our chosen $v(a), q(a)$ functions that result in a linear $v(a) \cdot q(a)$ We look at two alternate regimes, (i) $v(a) = \frac{a^2}{(1-a)}$ and $q(a) = \frac{1-a}{1+\delta}$ where $v(a) \cdot q(a)$ is convex, and (ii) $v(a) = \frac{\sqrt{a}}{(1-a)}$ and $q(a) = \frac{1-a}{1+\delta}$ where $v(a) \cdot q(a)$ is concave.



(a) Optimal revenue varies with δ when $c = 0.2$ (b) Optimal revenue varies with c when $\delta = 5$

Figure 11 **Optimal revenue when $v(a) = \frac{a^2}{(1-a)}$ and $q(a) = \frac{1-a}{1+\delta}$ as δ and c vary.** The left panel depicts how the optimal revenue varies with δ, and the right panel depicts how it varies with c when the valuation function has a higher growth than the original one while everything else stays the same. We see a similar behavior of revenue function.

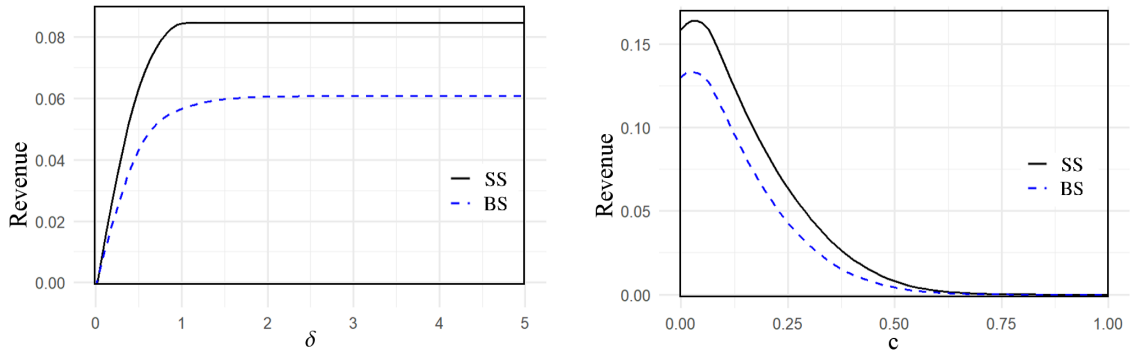
Fig. 11 shows that the revenue under both selling strategies drops. However, the relative gap increases signaling a stronger separate selling strategy. Looking at Fig. 12 where $v(a) = \frac{\sqrt{a}}{(1-a)}$ and $q(a) = \frac{1-a}{1+\delta}$ the revenue under both selling strategies increases, but the gap becomes relatively smaller.



(a) Optimal revenue varies with δ when $c = 0.2$ (b) Optimal revenue varies with c when $\delta = 5$

Figure 12 **Optimal revenue when $v(a) = \frac{\sqrt{a}}{(1-a)}$ and $q(a) = \frac{1-a}{1+\delta}$ as δ and c vary.**The left panel depicts how the optimal revenue varies with δ, and the right panel depicts how it varies with c when the valuation function has a lower growth than the original one while everything else stays the same. We see a similar behavior of revenue function.

We also look at multiple different distributions of candidate attractiveness given the original demand and probability functions $v(a) = \frac{a}{1-a}$, $q(a) = \frac{1-a}{1+\delta}$). The first distribution we look at in Fig. 13 is $\beta(2,5)$ where the attractiveness is more skewed toward zero, the revenue drops due to lower utility but the gap increases between two strategies. The second distribution we look at in Fig. 14 is $\beta(5,2)$ where the attractiveness is more skewed toward 1, the revenues increase due to higher utility, from higher attractiveness. However, the gap reduces between two strategies; making bundle selling strategy more viable. The third distribution we look at in Fig. 15 is $\beta(\frac{1}{2},\frac{1}{2})$ where the attractiveness is more similar to a uniform distribution with higher densities at both ends, resulting in similar optimal revenues to the uniform case.



(a) Optimal revenue varies with δ when $c = 0.2$ (b) Optimal revenue varies with c when $\delta = 5$

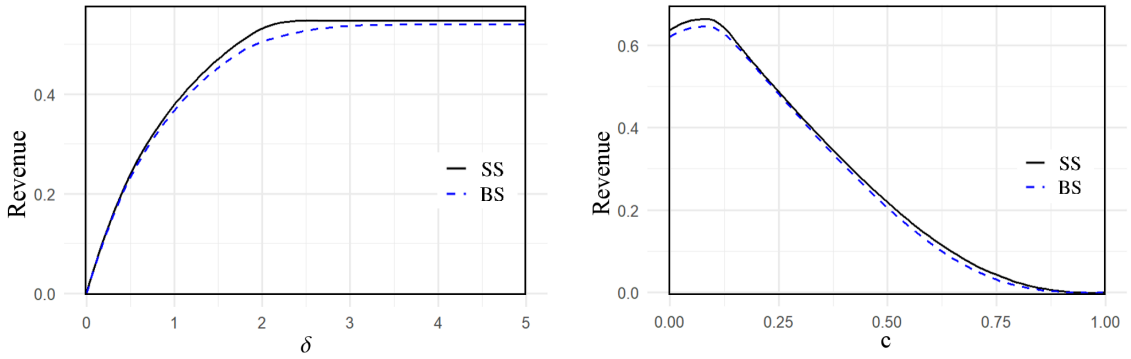
Figure 13 **Optimal revenue when we have $\beta(2,5)$ distribution as δ and c vary.** The left panel depicts how the optimal revenue varies with δ, and the right panel depicts how it varies with c when underlying attractiveness distribution is $\beta(2,5)$ rather than uniform while every other assumption remains the same. We see a similar behavior of the two strategies compare to original model assumptions.

Finally, we also look at the truncated normal distributions, with three different means with three different standard deviations.

Section 5 shows that as the average attractiveness of candidates increases and also as the uncertainty regrading this attractiveness decreases, the bundle selling strategy generates more revenue and can out perform than the separate selling strategy in extremes. **b**etter explanation

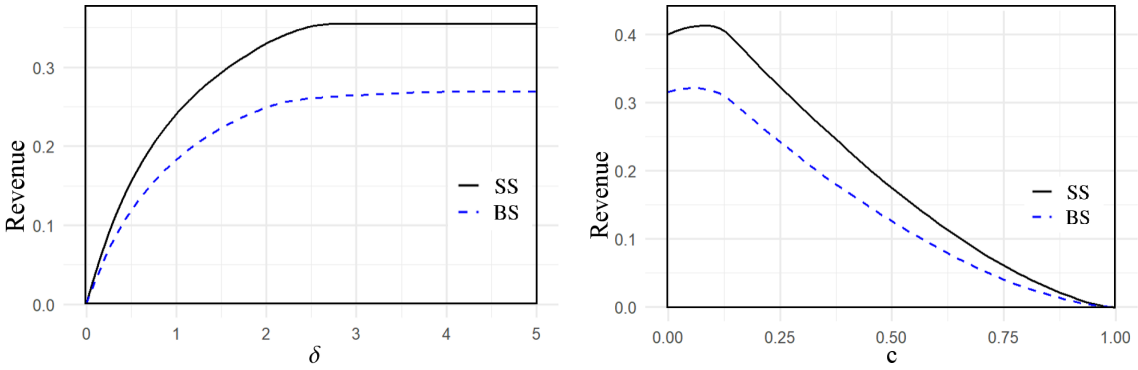
6. Conclusions and Future Directions

Many online dating apps generate revenue through *roses*, virtual products designed to increase a user's chance of matching. In this paper, we investigate how an online dating platform should offer roses to users. We develop a simple two-period model of forward-looking users engaged in costly search and consider three selling strategies: separate selling, bundle selling, and mixed selling. For separate selling and bundle selling, we characterize optimal user behavior, the platform's revenue-maximizing prices, and the optimal design of



(a) Optimal revenue varies with δ when $c = 0.2$ (b) Optimal revenue varies with c when $\delta = 5$

Figure 14 **Optimal revenue when we have $\beta(5,2)$ distribution as δ and c vary.** The left panel depicts how the optimal revenue varies with δ, and the right panel depicts how it varies with c when underlying attractiveness distribution is $\beta(5,2)$ rather than uniform while every other assumption remains the same. We see the gap between two strategies is closing.



(a) Optimal revenue varies with δ when $c = 0.2$ (b) Optimal revenue varies with c when $\delta = 5$

Figure 15 **Optimal revenue when we have $\beta(0.5,0.5)$ distribution as δ and c vary.** The left panel depicts how the optimal revenue varies with δ, and the right panel depicts how it varies with c when underlying attractiveness distribution is $\beta(0.5,0.5)$ rather than uniform while every other assumption remains the same. We see the gap between two strategies is higher in this case compare to Fig. 14.

roses. Under both strategies, optimal prices and revenues are non-decreasing in rose effectiveness and non-monotonic in search cost. Moreover, when the platform optimizes over both prices and rose effectiveness, separate selling yields higher revenue, user surplus, and social welfare than bundle selling. Our numerical analysis further shows that, with maximally effective roses, separate selling nearly matches mixed selling across all three metrics.

Taken together, our findings support selling roses separately and making them maximally effective. As roses are maximally effective when they are the de-facto only want to meet a candidate, users who do not

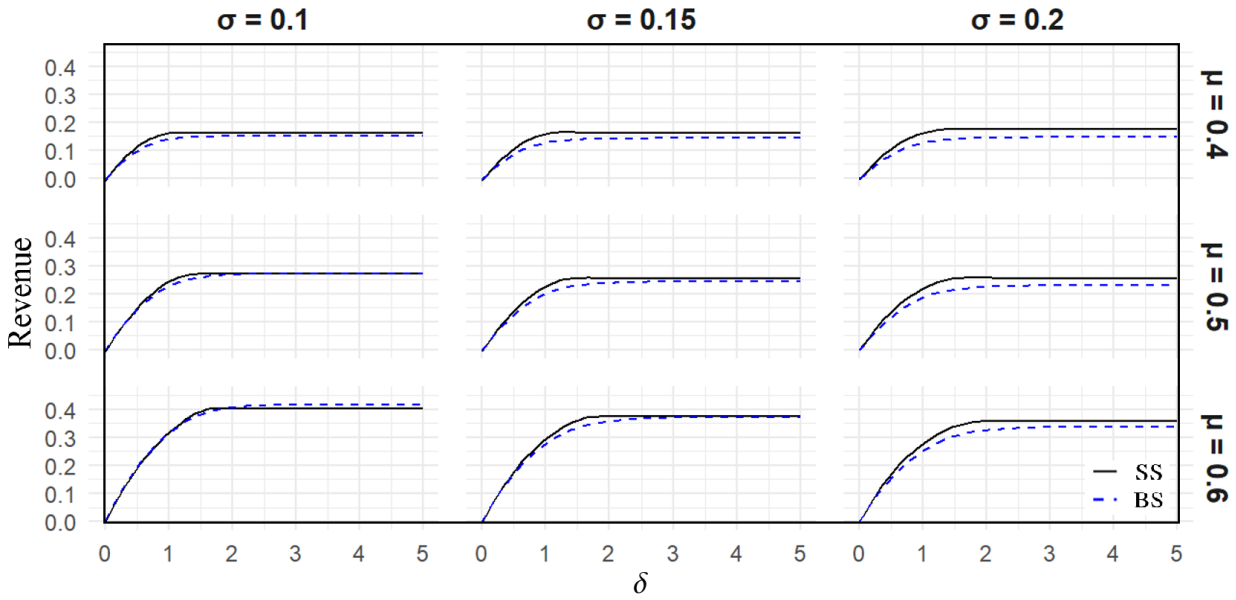


Figure 16 **Optimal revenue when attractiveness follows a truncated normal distribution as δ varies (c = 0.2).** We can see for some distribution parameters bundle selling strategy end up out performing separate selling strategy at the optimal design .

purchase a rose have no chance of matching, and separate selling reduces to a pay-per-message model which has seen some limited use in practice.

There are several potential avenues for extending our research. One is to incorporate additional sources of user churn and study how they affect optimal platform design. Such churn may introduce dynamic trade-offs between short-run monetization and long-run user retention. Second, our model could be expanded into a multi-period dynamic setting, potentially introducing a richer menu of roses. Finally, there are incentive considerations that our model does not address. In particular, users may not know whether purchasing a rose actually improved their chance of matching or whether their profile was truly prioritized or seen. Understanding how the platform's incentives and users' ability to verify rose effectiveness affect purchasing behavior and optimal design is an important direction for future research.

7. Data and Disclosure

All data and codes used to generate the analysis in this paper are publicly available at: https://github.com/efxing/Online_Matching_Platform

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EC.1. Model Notation

Table EC.1 Model Notation

Symbol	Description
a_i	Attractiveness of candidate in period i, drawn from $U[0,1]$
$v(a)$	User's valuation function, defined as $\frac{a}{1-a}$
$q(a)$	Match probability without rose: $\frac{1-a}{1+\delta}$
δ	Boosting factor of rose; probability modifier
c	Search cost incurred when interacting with a candidate
p_r	Price of a single rose (used in separate selling)
p_b	Price of a two-rose bundle (used in bundle selling)
$u^j_{s,i}(a)$	Utility to go in period $i \in \{1,2\}$ from swiping right(no request) under strategy $j \in \{SS, BS, MS\}$
$u^j_{n,i}(a)$	Utility to go in period $i \in \{1,2\}$ from swiping left(no request) under strategy $j \in \{SS, BS, MS\}$
$u^j_{r,i}(a)$	Utility to go in period $i \in \{1,2\}$ from sending a rose under strategy $j \in \{SS, MS\}$
$u^j_{b,1}(a)$	Utility to go in period 1 from buying and using the rose under bundle strategy $j \in \{BS, MS\}$
$\mathcal{R}^{SS}(p_r)$	Platform revenue under separate selling
$\mathcal{R}^{BS}(p_b)$	Platform revenue under bundle selling
$\mathcal{R}^{MS}(p_b, p_r)$	Platform revenue under mixed strategy
$a_{n,i}$, $a_{r,i}$	Thresholds for swiping right/buying rose in period i when $p_r < \min\{\frac{\delta}{1+\delta}, 1-c\}$
$a_{rn,i}$	Thresholds for buying rose in period i when $p_r \geq \min\{\frac{\delta}{1+\delta}, 1-c\}$
a_b	Threshold attractiveness above which user buys bundle
$a_{nb,1}$	Mixed bundle selling first period threshold where user swipes left or buy a bundle
$a_{br,1}$	Mixed bundle selling first period threshold where user buys a single rose or buys a bundle
$a_{nr,1}$	Mixed bundle selling first period threshold where user swipes left or buys a single rose
$\overline{c}(\delta)$, $\underline{c}(\delta)$	Cost thresholds under separate selling
$\overline{c}_b(\delta)$, $\underline{c}_b(\delta)$	Cost thresholds under bundle selling
$\mathcal{CS}^j$	user Surplus under strategy $j \in \{SS, BS, MS\}$
$\mathcal{SW}^j$	Social Welfare under strategy $j \in \{SS, BS, MS\}$

EC.2. Computation of Mixed Policy

Formally, we can express the second period utility as:

$$\mathbb{E}[u_2^{MS}] = \begin{cases} \mathbb{E}[u_{b,2}^{BS}], & \text{if they buy the bundle in the first period} \\ \mathbb{E}[u_2^{SS}], & \text{otherwise} \end{cases}$$

Now we can write the user's utility for each scenario.

$$u_1^{MS} = \begin{cases} u_{b,1}^{MS}(a_1) = (1+\delta)q(a_1)v(a_1) - c + (1-(1+\delta)q(a_1))\,\mathbb{E}[u_{b,2}^{BS}] - p_b & \text{if they decide to buy the bundle} \\ u_{r,1}^{MS}(a_1) = (1+\delta)q(a_1)v(a_1) - c + (1-(1+\delta)q(a_1))\mathbb{E}[u_2^{SS}] - p_r & \text{if they decide to buy a single rose} \\ u_{s,1}^{MS}(a_1) = q(a_1)v(a_1) - c + (1-q(a_1))\mathbb{E}[u_2^{SS}] & \text{if they decide to swipe right} \\ u_{n,1}^{MS}(a_1) = \mathbb{E}[u_2^{SS}] & \text{if they decide to swipe left} \end{cases}$$

In the following section we will only focus on the case where $\delta \to \infty$, as we showed earlier this was the optimally designed parameter, the following lemma characterizes the user's behavior.

Lemma EC.1 (User Behavior with Both Options with Maximum Visibility). *As $\delta \to \infty$, there exist unique thresholds*

$$a_{nb,1} = \frac{c + p_b + \mathbb{E}[u_2^{SS}]}{1 + \mathbb{E}[u_{b,2}^{BS}]},\ a_{nr,1} = \frac{c + p_r + \mathbb{E}[u_2^{SS}]}{1 + \mathbb{E}[u_2^{SS}]},\ \text{and } a_{br,1} = \frac{p_b - p_r}{\mathbb{E}[u_{b,2}^{BS}] - \mathbb{E}[u_2^{SS}]},$$

such that

(i) When $p_r > 1 - c$, and

(a) $p_b \le \frac{c^2-4c+3}{2}$, users swipe left if $a_1 < a_{nb,1}$ and purchase the bundle if $a_1 \ge a_{nb,1}$;

(b) $p_b > \frac{c^2-4c+3}{2}$, users swipe left.

(ii) When $p_r \le 1 - c$, and

(a) $p_b \le \underline{p}_b(p_r, c)$, users swipe left if $a_1 < a_{nb,1}$ and purchase the bundle if $a_1 \ge a_{nb,1}$;

(b) $\underline{p}_b(p_r, c) < p_b \le \overline{p}_b(p_r, c)$, users swipe left if $a_1 < a_{nr,1}$, purchase a rose if $a_{nr,1} \le a_1 < a_{br,1}$, and purchase the bundle if $a_1 \ge a_{br,1}$;

(c) $p_b > \overline{p}_b(p_r, c)$, users swipe left if $a_1 < a_{nr,1}$ and purchase a rose if $a_1 \ge a_{nr,1}$;

where $\underline{p}_b(p_r, c) = \frac{-p_r^4 + 4(1-c)p_r^3 - (5c^2-8c+5)p_r^2 - p_r(2c((c-2)c+3)-8)}{2p_r^2 - 4(1-c)p_r + 6 + 2c^2 - 4c}$, and $\overline{p}_b(p_r, c) = -\frac{1}{2}p_r^2 + (2-c)p_r$.

Our objective after this point is to numerically study how the revenue of mixed selling strategy behaves in comparison with the other cases where the user is limited to buy a rose or a bundle and the platform has already selected the optimal δ. Lemma EC.1 enables us to compute the revenue function as follow:

$$\mathcal{R}^{MS}(p_b, p_r) = \begin{cases} p_b(1 - a_{nb,1}) & \text{if } p_r > 1 - c, p_b < \frac{c^2-4c+3}{2}, \\ p_b(1 - a_{nb,1}) + p_r(1 - a_{rn,2})a_{nb,1} & \text{if } p_r \le 1 - c, p_b < \underline{p}_b(p_r, c), \\ p_b(1 - a_{br,1}) + p_r(a_{br,1} - a_{nr,1})(1 + \frac{(1-a_{rn,2})(a_{br,1}+a_{nr,1})}{2}) + p_r(1 - a_{rn,2})a_{nr,1} & \text{if } p_r \le 1 - c, \underline{p}_b(p_r, c) < p_b < \overline{p}_b(p_r, c), \\ p_r(1 - a_{nr,1}) + p_r(1 - a_{nr,1})(1 - a_{rn,2})\frac{1+a_{nr,1}}{2} + p_r(1 - a_{rn,2})a_{nr,1} & \text{if } p_r \le 1 - c, p_b > \overline{p}_b(p_r, c). \end{cases} \tag{EC.1}$$

We define the optimal mixed selling strategy's revenue $\mathcal{R}^{MS}$ as follow:

$$\mathcal{R}^{MS} = \max_{p_b, p_r} \mathcal{R}^{MS}(p_b, p_r)$$

EC.3. Omitted Proofs

In this section, we include proofs of all results omitted from the main body. All computations referenced in these proofs are conducted using Wolfram Mathematica version 13.1, and can be replicated using notebooks which are hosted at https://github.com/efxing/Online_Matching_Platform.

EC.3.1. Omitted Proofs from Section 3.1

Proof of Lemma 1. For any fixed p_r, users maximize their total expected utility by deciding to: send a rose (r), swipe right (s), or swipe left and not engage in the period (n). The user's utility-to-go in the first period from sending a rose is:

$$u_{r,1}^{SS}(a) = (a - p_r - c) + \mathbb{E}[u_2^{SS}] \Pr(\text{No Match}|\text{Rose}) = (a - p_r - c) + \mathbb{E}[u_2^{SS}]a,$$

and from swiping right but not sending a rose is:

$$u_{s,1}^{SS}(a) = \frac{a}{1+\delta} - c + \mathbb{E}[u_2^{SS}] \Pr(\text{No Match}|\text{No Rose}) = \frac{a}{1+\delta} - c + \mathbb{E}[u_2^{SS}] \left(1 - \frac{1-a}{1+\delta}\right).$$

Finally, the user's utility from not engaging in the first period is $\mathbb{E}[u_2^{SS}]$.

Note that the matching probability with or without sending a rose, $q(a)$, is linear in a. Therefore, the probability of not matching is also linear in a. Consequently, $u_{r,1}^{SS}(a)$ and $u_{s,1}^{SS}(a)$ are linear functions of a as they are the sums of linear functions. Further, we note that $u_{r,1}^{SS}(0) < u_{s,1}^{SS}(0) < u_{n,1}^{SS}(0)$, and $u_{r,1}^{SS}(1) > u_{s,1}^{SS}(1) > u_{n,1}^{SS}(1)$. Therefore, $u_{r,1}^{SS}(a)$ and $u_{s,1}^{SS}(a)$ cross $u_{n,1}^{SS}(a)$ once. Additionally, $u_{r,1}^{SS}(a)$ and $u_{s,1}^{SS}(a)$ cross each other once.

Solving $u_{s,1}^{SS}(a) = u_{r,1}^{SS}(a)$, $u_{s,1}^{SS}(a) = u_{r,1}^{SS}(a)$, and $u_{s,1}^{SS}(a) = u_{n,1}^{SS}(a)$, yields the threshold values characterized in the lemma.

Comparing these threshold values, we find that $a_{n,1} \le a_{r,1} \le 1$ if and only if $\delta c \le p_r \le \frac{\delta}{1+\delta}$. Furthermore, $a_{r,1} < a_{rn,1} < 1$ if and only if $p_r < \min\{\delta c, 1-c\}$, which completes the proof.

□

Proof of Lemma 2. From Lemma 1, when $p_r < \min\{\delta c, 1-c\}$ we have that:

$$\begin{aligned}
\mathcal{R}_l^{SS}(p_r) &= p_r \Pr(\text{Purchase in period 1}) + \Pr(\text{No match in the first period})\, p_r \Pr(\text{Purchase in period 2}) \\
&= p_r \Pr(a \in [a_{rn,1}, 1]) + p_r \Pr(a \in [a_{rn,2}, 1]) \Pr(\text{No match in the first period}) \\
&= p_r \Pr(a \in [a_{rn,1}, 1]) + p_r \Pr(a \in [a_{rn,2}, 1]) \left(1 - \Pr(a \in [a_{rn,1}, 1]) (1+\delta) \mathbb{E}[q(a)|a \in [a_{rn,1}, 1]]\right).
\end{aligned}$$

Additionally, when $p_r \in \left[\delta c, \delta/(1+\delta)\right)$,

$$\begin{aligned}
\mathcal{R}_g^{SS}(p_r) &= p_r \Pr(\text{Purchase in period 1}) + \Pr(\text{No match})\, p_r \Pr(\text{Purchase in period 2}) \\
&= p_r \Pr(a \in [a_{r,1}, 1]) + p_r \Pr(a \in [a_{r,2}, 1]) \Pr(\text{No match}) \\
&= p_r \Pr(a \in [a_{r,1}, 1]) \\
&\quad + p_r \Pr(a \in [a_{r,2}, 1]) \left(\Pr(a \in [0, a_{r,1})) (1+\delta) \mathbb{E}[q(a)|a \in [a_r, 1]] - \Pr(a \in [a_{n,1}, a_{r,1}]) \mathbb{E}[q(a)|a \in [a_{n,1}, a_{r,1}]]\right).
\end{aligned}$$

Plugging the values of $a_{rn,1}$, $a_{rn,2}$, $a_{r,1}$ and $a_{r,2}$ from Lemma 1 and calculating the second derivative, one can show that $\partial^2 \mathcal{R}_l^{SS}(p_r)/\partial p_r^2 < 0$ and $\partial^2 \mathcal{R}_g^{SS}(p_r)/\partial p_r^2 < 0$.

Furthermore, $\mathcal{R}_l^{SS}(\delta c) = \mathcal{R}_g^{SS}(\delta c)$ and

$$\frac{\partial \mathcal{R}_l^{SS}}{\partial p_r}(\delta c) - \frac{\partial \mathcal{R}_g^{SS}}{\partial p_r}(\delta c) = c + \frac{4c}{(c(1+\delta)(c\delta + c - 2) + 3)^2} > 0,$$

where we used the facts that $\delta > 0$ and $0 \le c < \frac{1}{1+\delta}$.

Since $\mathcal{R}_l^{SS}(p_r)$ and $\mathcal{R}_g^{SS}(p_r)$ are strictly concave, they meet at $p_r = \delta c$, and the derivative of $\mathcal{R}_l^{SS}(p_r)$ is greater than the derivative of $\mathcal{R}_l^{SS}(p_r)$ at the point they meet, we conclude that $\mathcal{R}^{SS}(p_r)$ is concave in p_r.

Finally, when $\delta c > \frac{\delta}{1+\delta}$, $\mathcal{R}^{SS} = \mathcal{R}_l^{SS}$, which is concave. □

Proof of Theorem 1. **(i)** Recall from Lemma 2 that $\mathcal{R}^{SS}(p_r)$, $\mathcal{R}_g^{SS}(p_r)$, and $\mathcal{R}_l^{SS}(p_r)$ are concave functions, and thus have unique maximizing prices. Let $p_{rg}^* := \arg\max_{p_r} \mathcal{R}_g^{SS}(p_r)$, $p_{rl}^* := \arg\max_{p_r} \mathcal{R}_l^{SS}(p_r)$, and $p_r^* := \arg\max_{p_r} \mathcal{R}^{SS}(p_r)$. Revenue function $\mathcal{R}^{SS}(p_r)$ is equal to $\mathcal{R}_l^{SS}(p_r)$ when $p_r < \delta c$, and equal to $\mathcal{R}_g^{SS}(p_r)$ when $p_r \geq \delta c$. Note that from the concavity of $\mathcal{R}^{SS}(p_r)$, we have $p_{rl}^* \leq p_{rg}^*$. This implies that there are three possible values for p_r^*: (1) if $\delta c > \min\{p_{rl}^*, p_{rg}^*\}$, then p_r^* must equal p_{rl}^*; (2) if $\delta c < \min\{p_{rl}^*, p_{rg}^*\}$ then p_r^* must equal p_{rg}^*; (3) if $\delta c \in [p_{rg}^*, p_{rl}^*]$, then $\mathcal{R}^{SS}(p_r)$ is strictly increasing for $p_r < \delta c$ and decreasing for $p_r \geq \delta c$. From the continuity of $\mathcal{R}^{SS}(p_r)$, we have $p_r^* = \delta c$.

Note that since $\mathcal{R}_g^{SS}(p_r)$ and $\mathcal{R}_l^{SS}(p_r)$ are concave we can define $\underline{c}(\delta)$ as the maximum value of c such that $\frac{\partial \mathcal{R}_l^{SS}}{\partial p_r}|_{p_r=\delta c} \geq 0$ and $\overline{c}(\delta)$ as the minimum value of c such that $\frac{\partial \mathcal{R}_g^{SS}}{\partial p_r}|_{p_r=\delta c} \leq 0$. This completes proof of Part (i).

(ii) As we saw earlier the optimal price p_r^* is equal to p_{rg}^* when $c \leq \underline{c}$, it is equal to δc when $\underline{c} < c \leq \overline{c}$,and finaly it is equal to p_{rl}^* when $\overline{c} < c$. We show that the derivative of the optimal price with respect to search cost is positive when $c < \overline{c}$ and negative when $c > \overline{c}$. Namely $\frac{\partial p_{rg}^*}{\partial c} > 0$ if $c \leq \underline{c}$, $\frac{\partial \delta c}{\partial c} = \delta > 0$, and $\frac{\partial p_{rl}^*}{\partial c} < 0$ if $c \geq \overline{c}$.

□

Proof of Theorem 2. We will prove the two cases of the theorem separately.

(i) First note that

$$\mathcal{R}_l^{SS}(p_r) = \frac{p_r\left(1-c-p_r\right)\left(p_r\left(2c+p_r-2\right)\left(p_r\left(2c+p_r-2\right)+2(c-2)c+6\right)+(c-2)c((c-2)c+6)+13\right)}{\left(p_r\left(2c+p_r-2\right)+c^2-2c+3\right)^2},$$

which is independent of δ. Thus, $\mathcal{R}_l^{SS} = \max_{p_r} \mathcal{R}_l^{SS}(p_r)$ is also independent of δ. Additionally, it is straightforward to show by CAS that $\frac{\partial \mathcal{R}_g^{SS}(p_{rg}^*)}{\partial \delta} > 0$. Since $\mathcal{R}_g^{SS}$ is a strictly increasing function and $\mathcal{R}_l^{SS}$ is constant in δ, they cross at most once. The result then follows from the fact that $\mathcal{R}_l^{SS}(\delta c) = \mathcal{R}_l^{SS}(\delta c)$.

(ii) We note that $\partial \mathcal{R}^{SS}/\partial c|_{c=c^*} = 0$, where

$$\begin{aligned}
c^* = &\text{Root}[c^7\left(2\delta^7+14\delta^6+42\delta^5+70\delta^4+70\delta^3+42\delta^2+14\delta+2\right)\\
&+c^6\left(-13\delta^6-78\delta^5-195\delta^4-260\delta^3-195\delta^2-78\delta-13\right)\\
&+c^5\left(48\delta^5+240\delta^4+480\delta^3+480\delta^2+240\delta+48\right)\\
&+c^4\left(-109\delta^4-436\delta^3-654\delta^2-436\delta-109\right)\\
&+c^3\left(162\delta^3+486\delta^2+486\delta+162\right)\\
&+c^2\left(-159\delta^2-318\delta-159\right)\\
&+c^1(124\delta+124)-39].
\end{aligned}$$

The proof then follows from observing that $\partial \mathcal{R}^{SS}/\partial c < 0$ for $c < c^*$ and $\partial \mathcal{R}^{SS}/\partial c < 0$ for $c > c^*$.

□

EC.3.2. Omitted Proofs from Section 3.2

Proof of Lemma 3. A user would choose to purchase a bundle if she receives a higher utility than choosing her outside option and swiping right without buying a bundle, i.e., $u^{BS}_{b,1}(a_1) \geq u^{BS}_{n,1}$ and $u^{BS}_{b,1}(a_1) \geq u^{BS}_{s,1}(a_1)$. Similar to Lemma 1, we observe that $u^{BS}_{n,1}$ is independent of a. Also, $u^{BS}_{b,1}(a_1)$ and $u^{BS}_{s,1}(a_1)$ are increasing functions of a_1. Therefore, it is sufficient to show that $\partial u^{BS}_{b,1}(a_1)/\partial a_1 - \partial u^{BS}_{s,1}(a_1)/\partial a_1 > 0$. We have the following two cases

Case 1. $c < \frac{1}{1+\delta}$. We have

$$\begin{aligned}\partial u^{BS}_{b,1}(a_1)/\partial a_1 - \partial u^{BS}_{s,1}(a_1)/\partial a_1 &= \frac{c^2-2c+3}{2} - \frac{c(1+\delta)(c\delta+c-2)+2\delta+3}{2(1+\delta)^2} \\ &= \frac{\delta(4+3\delta-2c(1+\delta)}{2(1+\delta)^2} \geq 0.\end{aligned}$$

Case 2. $c > \frac{1}{1+\delta}$. In this case,

$$\partial u^{BS}_{b,1}(a_1)/\partial a_1 - \partial u^{BS}_{s,1}(a_1)/\partial a_1 = \frac{c^2-2c+3}{2} - \frac{1}{1+\delta} > 0,$$

Which is what we desired to show.

Having established the uniqueness of the crossing point, a_b is calculated from $u^{BS}_{b,1}(a_1) = u^{BS}_{s,1}(a_1)$ and $u^{BS}_{b,1}(a_1) = u^{BS}_{n,1}$ for each case, and getting the maximum of the two solutions.

□

Proof of Lemma 4. Recall from Eq. (3) that $\mathcal{R}^{BS}(p_b) := p_b(1-a_b)^+$, where a_b is defined in Lemma 3. Note that a_b is increasing in p_b and it is not optimal for the firm to set p_b such that $a_b = 1$. Focusing, on the region where $a_b < 1$, we have

Case 1: $c < \frac{1}{1+\delta}$. In this case,

$$a_b = \max\{\frac{\delta(1-c(1+\delta))^2 + 2p_b(1+\delta)^2}{\delta(1+(1+\delta)(3-2c))}, \frac{1+c^2(1+\delta)^2+2p_b(1+\delta)}{(c^2-2c+3)(1+\delta)}\}.$$

Hence,

$$\mathcal{R}^{BS}(p_b) = p_b + \min\{-p_b\left(\frac{\delta(1-c(1+\delta))^2 + 2p_b(1+\delta)^2}{\delta(1+(1+\delta)(3-2c))}\right), -p_b\left(\frac{1+c^2(1+\delta)^2+2p_b(1+\delta)}{(c^2-2c+3)(1+\delta)}\right)\}.$$

Since the functions inside the minimization are quadratic and concave, and that the concavity is preserved under minimization and summation with a linear function, we conclude that $\mathcal{R}^{BS}(p_b)$ is concave when $c < \frac{1}{1+\delta}$.

Case 2: $c > \frac{1}{1+\delta}$. In this case,

$$a_b = \frac{2(c+p_b)}{c^2-2c+3}.$$

Hence,

$$\mathcal{R}^{BS}(p_b) = p_b - \frac{2p_b(c+p_b)}{c^2-2c+3},$$

from which it is straightforward to see that $\mathcal{R}^{BS}(p_b)$ is concave.

□

Proof of Theorem 3. **(i)** From Lemma 4, $\mathcal{R}^{BS}(p_b)$ has a unique maximizing price. We will proceed similar to the proof of Lemma 4 by considering the following cases:

Case 1: $c < \frac{1}{1+\delta}$. In this case, recall that the revenue function is:

$$\mathcal{R}^{BS}(p_b) = \begin{cases} p_b - p_b\left(\frac{1+c^2(1+\delta)^2+2p_b(1+\delta)}{\left(c^2-2c+3\right)(1+\delta)}\right) & \text{if } p_b < \bar{p}_b \\ p_b - p_b\left(\frac{\delta(1-c(1+\delta))^2+2p_b(1+\delta)^2}{\delta(1+(1+\delta)(3-2c))}\right) & \text{if } \bar{p}_b \le p_b \le \frac{\delta\left(3-c^2(1+\delta)\right)}{2(1+\delta)}, \end{cases} \tag{EC.2}$$

where $\bar{p}_b = \frac{\delta-c\delta(1+\delta)\left(c^3(1+\delta)^2+(c(3-2c)-6)(1+\delta)+c\right)}{2(1+\delta)\left(1+2(1-c)(1+\delta)+c^2(1+\delta)^2\right)}$. Let $\mathcal{R}_1^{BS}(p_b) := p_b - p_b\left(\frac{1+c^2(1+\delta)^2+2p_b(1+\delta)}{\left(c^2-2c+3\right)(1+\delta)}\right)$ and $\mathcal{R}_2^{BS}(p_b) := p_b - p_b\left(\frac{\delta(1-c(1+\delta))^2+2p_b(1+\delta)^2}{\delta(1+(1+\delta)(3-2c))}\right)$.

We observe that $\mathcal{R}_1^{BS}(p_b)$ and $\mathcal{R}_2^{BS}(p_b)$ are maximized at $p_{b1}^* = \frac{\delta+(1+\delta)(2(1-c)-\delta c^2)}{4(1+\delta)}$ and $p_{b2}^* = \frac{\delta(3-(1+\delta)c^2)}{4(1+\delta)}$, respectively. From the concavity of the revenue function, it follows that

$$p_b^* = \begin{cases} p_{b1}^*, & \text{if } \partial\mathcal{R}_1^{BS}(p_b)/\partial p_b|_{p_b=\bar{p}_b} < 0 \\ p_{b2}^*, & \text{if } \partial\mathcal{R}_2^{BS}(p_b)/\partial p_b|_{p_b=\bar{p}_b} > 0 \\ \bar{p}_b, & \text{otherwise.} \end{cases} \tag{EC.3}$$

Checking the conditions in Equation (EC.3) yield that

$$p_b^* = \begin{cases} \frac{\delta(3-(1+\delta)c^2)}{4(1+\delta)}, & \text{if } c \le \underline{c}_b \\ \frac{\delta-c\delta(1+\delta)(c(c(1+\delta)(c\delta+c-2)+3\delta+4)-6(1+\delta))}{2(1+\delta)(3+2\delta-2c(1+\delta)+c^2(1+\delta)^2)}, & \text{if } \underline{c}_b < c \le \bar{c}_b \\ \frac{\delta+(1+\delta)(2(1-c)-\delta c^2)}{4(1+\delta)}, & \text{if } \bar{c}_b < c \le \frac{1}{1+\delta}, \end{cases}$$

where

$$\underline{c}_b(\delta) \triangleq \text{Root}\left[c^4(1+\delta)^3 - 2c^3(1+\delta)^2 + c^2\left(7\delta^2+15\delta+8\right) - 6c(1+\delta)(2\delta+3) + 6\delta + 7, 1\right],$$

$$\bar{c}_b(\delta) \triangleq \text{Root}\left[c^4\delta(1+\delta)^3 - 2c^3(1+\delta)^2(2\delta+1) + c^2\left(7\delta^3+21\delta^2+20\delta+6\right) - 2c(1+\delta)^2(6\delta+5) + 6\delta^2+11\delta+6, 1\right].$$

Case 2: $\frac{1}{(1+\delta)} < c < 1$. The revenue function is:

$$\mathcal{R}^{BS}(p_b) = p_b - \frac{2p_b(c+p_b)}{c^2-2c+3},$$

which is maximized at $p_b^* = \frac{(1-c)(3-c)}{4}$. Combining the two cases gives the optimal price p_b^*.

(ii) The result follows from checking that $\frac{\partial p_b^*}{\partial \delta} > 0$. Additionally, $\lim_{\delta\to\infty} \overline{c}_b = 0$. Consequently,

$$\lim_{\delta\to\infty} p_b^* = \frac{(1-c)(3-c)}{4}. \tag{EC.4}$$

(iii) Taking the derivative the p_b^* with respect to c, we have

$$\frac{\partial p_b^*}{\partial c} = \begin{cases} -\frac{\delta c}{2} < 0 & \text{if } c \le \underline{c}_b \\ \frac{\delta\left(c^5\left(-(\delta+1)^4\right)+4c^4(\delta+1)^3-2c^3(\delta+1)^2(2\delta+5)+c^2\left(-3\delta^3+13\delta+10\right)-c(6\delta(\delta+3)+13)+3\delta(2\delta+5)+10\right)}{(c(\delta+1)(c\delta+c-2)+2\delta+3)^2} > 0 & \text{if } \underline{c}_b < c \le \overline{c}_b \\ -\frac{1+c\delta}{2} < 0 & \text{if } \overline{c}_b < c \le \frac{1}{1+\delta} \\ -\frac{2-c}{2} < 0 & \text{if } \frac{1}{1+\delta} \le c < 1. \end{cases}$$

□

Proof of Theorem 4. **(i)** Follows from pllugging p_b^* into the revenue function.

(ii) We note that $\mathcal{R}^{BS}$ is independent of δ for $c > 1/(1+\delta)$. We can also verify that $\partial\mathcal{R}^{BS}/\partial\delta \ge 0$ for all pieces of $\mathcal{R}^{BS}$. Finally, we note that $\mathcal{R}^{BS}$ is continuous in δ. Thus, $\mathcal{R}^{BS}$ is nondecreasing in δ.

(iii) Taking the derivative of $\mathcal{R}^{BS}$ with respect to c, we have

$$\frac{\partial\mathcal{R}^{BS}}{\partial c} = \begin{cases} > 0 & \text{if } c \le \frac{4+3\delta-\sqrt{9\delta^2+15\delta+7}}{3(1+\delta)} \\ < 0 & \text{if } c > \frac{4+3\delta-\sqrt{9\delta^2+15\delta+7}}{3(1+\delta)}. \end{cases}$$

□

Proof of Lemma EC.1. Consider the case where $\delta = \infty$. First, we show that if the user does not purchase a rose, she would never swipe right, i.e., $u_{s,1}^{MS} < u_{n,1}^{MS}$. To see this note that

$$u_{s,1}^{MS} = \begin{cases} \frac{(1-c-p_r)^2}{2} - 2c & \text{if } p_r < 1-c \\ -c & \text{if } p_r > 1-c, \end{cases}$$

and

$$u_{n,1}^{MS} = \begin{cases} \frac{(1-c-p_r)^2}{2} & \text{if } p_r < 1-c \\ 0 & \text{if } p_r > 1-c. \end{cases}$$

Hence, $u_{s,1}^{MS} < u_{n,1}^{MS}$.

Part (i) When $p_r > 1-c$. We have

$$u_1^{MS} = \begin{cases} u_{b,1}^{MS} = \frac{a_1(c^2-2c+3)-2(c+p_b)}{2} & \text{if they decide to buy the bundle} \\ u_{r,1}^{MS} = a_1 - c - p_r, & \text{if they decide to buy a single rose} \\ u_{n,1}^{MS} = 0, & \text{if they decide to swipe left} \end{cases}$$

Solving $u_{n,1}^{MS} = u_{r,1}^{MS}$, $u_{b,1}^{MS} = u_{n,1}^{MS}$, and $u_{b,1}^{MS} = u_{r,1}^{MS}$, we obtain $a_{nr,1} = p_r + c$, $a_{nb,1} = \frac{2(c+p_b)}{c^2-2c+3}$, and $a_{br,1} = \frac{2(p_b-p_r)}{(c-1)^2}$. It follows that $a_{nr,1} > a_{nb,1}$. Moreover, $u_{r,1}^{MS}(a_{br,1}) = u_{b,1}^{MS}(a_{br,1}) = \frac{2(p_b-p_r)}{(c-1)^2} - c - p_r < 0$. Additionally, $a_{nb,1} \leq 1$ holds whenever $p_b \leq \frac{c^2-4c+3}{2}$.

Therefore, in this case, the users would either swipe left or buy a bundle when $p_b \leq \frac{c^2-4c+3}{2}$, which we desired to show.

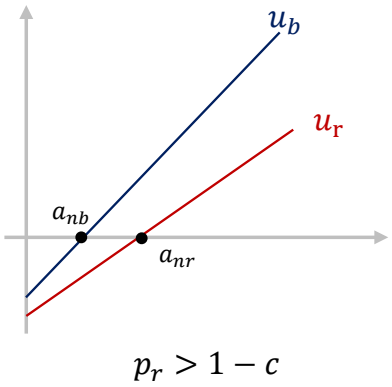


Figure EC.1 Depicted is the utility a user garners when they either buy a bundle, or swipe left when $p_r > 1 - c$.

Part (ii) When $p_r \leq 1 - c$. In this case,

$$u_1^{MS} = \begin{cases} u_{b,1}^{MS} = \frac{a_1(c^2-2c+3)-2(c+p_b)}{2} & \text{if they decide to buy the bundle} \\ u_{r,1}^{MS} = a_1 - c - p_r + \frac{1}{2}a_1(-1+c+p_r)^2, & \text{if they decide to buy a single rose} \\ u_{n,1}^{MS} = \frac{1}{2}(c+p_r-1)^2 & \text{if decide to they swipe left} \end{cases}$$

Thus, $a_{nr,1} = \frac{(c+p_r)^2+1}{c^2+2c(p_r-1)+(p_r-2)p_r+3}$, $a_{nb,1} = \frac{(c+p_r)^2+2p_b-2p_r+1}{c^2-2c+3}$, and $a_{br,1} = \frac{2(p_r-p_b)}{p_r(2c+p_r-2)}$.

We have the following three cases:

Case 1. If $p_b \leq \underline{p}_b$, then $a_{nb,1} < a_{nr,1}$. Further, $a_{nb,1} \leq 1$, and $u_{b,1}^{MS}(a_{br,1}) = u_{r,1}^{MS}(a_{br,1}) \leq u_n^{MS}$.

Case 2. If $\underline{p}_b < p_b \leq \overline{p}_b$, then $a_{nr,1} < a_{nb,1} < a_{br,1} < 1$.

Case 3. If $p_b > \overline{p}_b$, then $a_{nr,1} < a_{nb,1}$, and $a_{rn,1} < a_{bn,1} < a_{br,1} \leq 1$.

□

EC.3.3. Omitted Proofs from Section 4

Proof of Theorem 5 From the proof of Lemma 2,

$$\lim_{\delta\to\infty} \mathcal{R}^{SS}(p_r) = p_r(1-a_{rn,1}) + p_r(1-a_{rn,2})a_{rn,1}\frac{1-a_{rn,1}}{2},$$

where $a_{rn,1} = \frac{c+p_r+\mathbb{E}[u_2^{SS}]}{1+\mathbb{E}[u_2^{SS}]}$ and $a_{rn,2} = c + p_r$.

Substituting these terms in $\mathcal{R}^{SS}(p_r)$, we derive

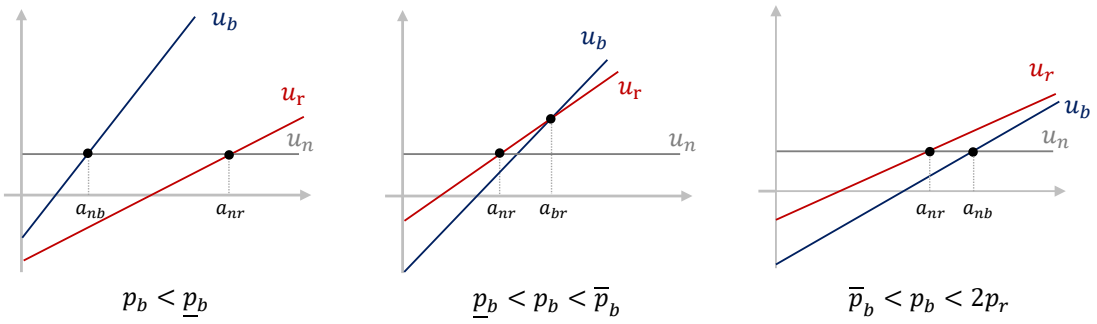


Figure EC.2 Depicted is the utility a user garners when they either buy a bundle, buy a rose, just swipe right, or swipe left when $p_r < 1-c$, depending on the value of p_b, p_r and c.

$$\lim_{\delta\to\infty}\mathcal{R}^{SS}(p_r)=\frac{p_r\left(p_r-(1-c)\right)\left(p_r\left(p_r-2(1-c)\right)-2\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}](3+\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}])-3-c(2-c)\right)}{2(1+\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}])^2},$$

From Lemma 1, $\lim\limits_{\delta\to\infty}p_r^*\le 1-c$. Therefore, we can focus on the region where $p_r\le 1-c$. In this region, $\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}]=\frac{(1-c-p_r)^2}{2}\le\frac{(1-c)^2}{2}$. Taking the derivative of $\lim\limits_{\delta\to\infty}\mathcal{R}^{SS}(p_r)$ with respect to $\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}]$, we obtain

$$\frac{\partial\lim\limits_{\delta\to\infty}\mathcal{R}^{SS}(p_r)}{\partial\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}]}=-\frac{p_r\left(1-c-p_r\right)\left(\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}]+c(2-c)+p_r\left(2(1-c)-p_r\right)\right)}{(1+\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}])^3}<0.$$

Since $\mathcal{R}^{SS}(p_r)$ is decreasing in $\lim\limits_{\delta\to\infty}\mathbb{E}[u_2^{SS}]$ and $\mathbb{E}[u_2^{SS}]\le\frac{(1-c)^2}{2}$, then

$$\begin{aligned}\mathcal{R}^{SS}(p_r)&\ge\frac{p_r\left(p_r-(1-c)\right)\left(p_r\left(p_r-2(1-c)\right)-2\frac{(1-c)^2}{2}(3+\frac{(1-c)^2}{2})-3-c(2-c)\right)}{2(1+\frac{(1-c)^2}{2})^2}\\&=\frac{2p_r^4-6(1-c)p_r^3+\left(-c^4+4c^3-6c^2+4c-9\right)p_r^2+\left(-c^5+5c^4-14c^3+22c^2-25c+13\right)p_r}{\left(c^2-2c+3\right)^2}\\&\ge\frac{-6(1-c)p_r^3+\left(-c^4+4c^3-6c^2+4c-9\right)p_r^2+\left(-c^5+5c^4-14c^3+22c^2-25c+13\right)p_r}{\left(c^2-2c+3\right)^2}:=L_2(p_r),\end{aligned}\tag{EC.5}$$

where the last inequality followed from dropping $2p_r^4$ from the numerator. Since Equation (EC.5) holds for any $p_r\le 1-c$, it also holds at the optimal price. In other words,

$$L_2(p_r^*)=-\frac{B(-A+(c-2)c((c-2)c+2)+9)}{972(c-1)^2(c^2-2c+3)^2}\le\mathcal{R}^{SS}(p_r^*)=\mathcal{R}^{SS},$$

where $A=\sqrt{(c^2-2c+3)((c-2)c+5)((c-2)c((c-2)c+14)+21)}$ and $B=(c-2)c((c-2)c(-A+(c-2)c((c-2)c+40)+274)-2A+720)-9(A-61)$.

Furthermore, from Theorem 4,

$$\lim_{\delta\to\infty}\mathcal{R}^{BS}=\frac{\left((1-c)(3-c)\right)^2}{8\left(c^2-2c+3\right)}\le L_2(p_r^*)\le\mathcal{R}^{SS},$$

which is what we desired to show. □

Proof of Theorem 6. As a preliminary, we will first compute the expected user's utility for both strategies. For separate selling, the expected user's utility is a piecewise function based on the value of p_r that determines the user's behavior that we previously found in Lemma 1.

$$\mathbb{E}[u^{SS}(p_r)]=\begin{cases}\int_{a_{rn,1}}^{1}u_{r,1}^{SS}(a_1)\,da_1+\int_0^{a_{rn,1}}u_{n,1}^{SS}(a_1)\,da_1 & \text{if } p_r<\min\{\delta c,1-c\},\\ \int_{a_{r,1}}^{1}u_{r,1}^{SS}(a_1)\,da_1+\int_{a_{n,1}}^{a_{r,1}}u_{s,1}^{SS}(a_1)\,da_1+\int_0^{a_{n,1}}u_{n,1}^{SS}(a_1)\,da_1 & \text{if } \delta c\le p_r\le\frac{\delta}{1+\delta}.\end{cases}$$

By substituting the optimal price p_r^* in the equation, we can compute the user surplus as a piecewise function of c, δ, $p_{rl}^*(c,\delta)$, and $p_{rg}^*(c,\delta)$, where each piece depends on the value of c.

$$\begin{aligned}CS^{SS}&=\begin{cases}\int_{a_{r,1}}^{1}(a_1-p_{rg}^*-c)+\mathbb{E}[u_2^{SS}]a_1\,da_1+\int_{a_{n,1}}^{a_{r,1}}\frac{a_1}{1+\delta}+\mathbb{E}[u_2^{SS}]\,\frac{\delta-a_1}{1+\delta}-c\,da_1+\int_0^{a_{n,1}}\mathbb{E}[u_2^{SS}]\,da_1 & \text{if } c\le\underline{c}(\delta)\\ \int_{a_{rn,1}}^{1}(a_1-\delta c-c)+\mathbb{E}[u_2^{SS}]a_1\,da_1+\int_0^{a_{rn,1}}\mathbb{E}[u_2^{SS}]\,da_1 & \text{if } \underline{c}(\delta)<c\le\overline{c}(\delta)\\ \int_{a_{rn,1}}^{1}(a_1-p_{rl}^*-c)+\mathbb{E}[u_2^{SS}]a_1\,da_1+\int_0^{a_{rn,1}}\mathbb{E}[u_2^{SS}]\,da_1 & \text{if } \overline{c}(\delta)<c.\end{cases}\\&=\begin{cases}\frac{c(c\delta+c-2)}{2}-\frac{2\delta}{\delta(c(c\delta+c-2)+3)+(1+\delta){p_{rg}^*}^2-2\delta p_{rg}^*}+\frac{1+\delta}{2\delta}{p_{rg}^*}^2-p_{rg}^*+\frac{3}{2} & \text{if } c\le\underline{c}(\delta),\\ \frac{(c\delta+c-1)^2(c(\delta+1)(c\delta+c-2)+5)}{2c(\delta+1)(c\delta+c-2)+6} & \text{if } \underline{c}(\delta)<c\le\overline{c}(\delta),\\ \frac{(c+p_{rl}^*-1)^2\left(c^2+2c(p_{rl}^*-1)+(p_{rl}^*-2)p_{rl}^*+5\right)}{2\left(c^2+2c(p_{rl}^*-1)+(p_{rl}^*-2)p_{rl}^*+3\right)} & \text{if } \overline{c}(\delta)<c.\end{cases}\end{aligned}$$

Similarly, for bundle selling, let a_s be the attractiveness at which a user derives equal utility from purchasing the bundle and swiping right (i.e., $u_{b,1}^{BS}(a_s)=u_{s,1}^{BS}(a_s)$). Based on the user behavior established in Lemma 3, we have:

$$\mathbb{E}[u^{BS}(p_b)]=\int_{a_b}^{1}u_{b,1}^{BS}(a_1)\,da_1+\int_{a_s}^{a_b}u_{s,1}^{BS}(a_1)\,da_1+\int_0^{a_s}u_{n,1}^{BS}(a_1)\,da_1.$$

When the platform sets the optimal price p_b^* we can write the user's surplus as a function of c and δ

$$\begin{aligned}CS^{BS}&=\begin{cases}\int_{a_b}^{1}u_{b,1}^{BS}(a_1)\,da_1+\int_{a_s}^{a_b}u_{s,1}^{BS}(a_1)\,da_1+\int_0^{a_s}u_{n,1}^{BS}(a_1)\,da_1 & \text{if } c\le\underline{c}_b\\ \int_{a_b}^{1}u_{b,1}^{BS}(a_1)\,da_1+\int_0^{a_b}u_{n,1}^{BS}(a_1)\,da_1 & \text{if } \underline{c}_b<c\le\overline{c}_b\\ \int_{a_b}^{1}u_{b,1}^{BS}(a_1)\,da_1+\int_0^{a_b}u_{n,1}^{BS}(a_1)\,da_1 & \text{if } \overline{c}_b<c<\frac{1}{1+\delta}\\ \int_{a_b}^{1}u_{b,1}^{BS}(a_1)\,da_1+0 & \text{if } \frac{1}{1+\delta}<c<1\end{cases}\\&=\begin{cases}CS_B & \text{if } c\le\underline{c}_b,\\ \frac{(c\delta+c-1)^2\left(c^4(\delta+1)^4-4c^3(\delta+1)^3+6c^2(\delta+2)(\delta+1)^2-4c(\delta+2)^2(\delta+1)+2\delta(\delta(3\delta+11)+15)+15\right)}{2(\delta+1)(c(\delta+1)(c\delta+c-2)+2\delta+3)^2} & \text{if } \underline{c}_b<c\le\overline{c}_b,\\ \frac{c^4(\delta+1)^2(\delta(\delta+8)+8)-4c^3(\delta+1)^2(3\delta+8)+2c^2(\delta+1)(\delta(9\delta+40)+34)-12c(\delta+1)(5\delta+6)+9\delta(\delta+4)+28}{16((c-2)c+3)(\delta+1)^2} & \text{if } \overline{c}_b<c\le\frac{1}{1+\delta},\\ \frac{((1-c)(3-c))^2}{16((c-2)c+3)} & \text{if } \frac{1}{1+\delta}<c<1.\end{cases}\end{aligned}$$

When δ approaches ∞, we have $c > \overline{c}(\delta)$. Hence, from Section 4.2,

$$\lim_{\delta\to\infty} CS^{SS}(p_r) = \frac{(1-c-p_r)^2\left(c^2+2c(p_r-1)+(p_r-2)p_r+5\right)}{2\left(c^2+2c(p_r-1)+(p_r-2)p_r+3\right)}, \text{and}$$
$$\lim_{\delta\to\infty} CS^{BS}(p_b^*) = \frac{\left((1-c)(3-c)\right)^2}{16(c^2-2c+3)}.$$

First, we show that $\lim_{\delta\to\infty} CS^{SS}(p_r)$ is decreasing in p_r. Taking the derivative with respect to p_r, we have

$$\begin{aligned}\frac{\partial \lim_{\delta\to\infty} CS^{SS}(p_r)}{\partial p_r} &= -\frac{4(1-c-p_r)}{\left(c^2+2c(p_r-1)+(p_{rl}-2)p_r+3\right)^2} - (1-c-p_r)\\ &= -(1-c-p_{rl})\left(\frac{4}{\left(c^2+2c(p_r-1)+(p_{rl}-2)p_r+3\right)^2}+1\right) < 0,\end{aligned} \tag{EC.6}$$

which establishes the decreasing property we desired to show.

Since the closed form for $p_r^* = p_{rl}^*$ is complex, next, we find an upper bound for the optimal price p_{rl}^*. Let $p_{rl}^u = 0.55(1-c)$. We have

$$\left.\frac{\partial \mathcal{R}_l^{SS}(p_r)}{\partial p_r}\right|_{p_r=p_{rl}^u} < 0.$$

From Lemma 2, $\mathcal{R}_l^{SS}(p_r)$ is strictly concave in p_r on its support, and the optimal solution is an interior point. Hence, we have $p_{rl}^* < p_{rl}^u$.

Additionally, since $CS^{SS}(p_{rl})$ is decreasing in p_{rl}, $\lim_{\delta\to\infty} CS^{SS}(p_{rl}^u) < \lim_{\delta\to\infty} CS^{SS}(p_{rl}^*)$. Hence,

$$\begin{aligned}\lim_{\delta\to\infty} CS^{SS}(p_{rl}^*) - \lim_{\delta\to\infty} CS^{BS}(p_b^*) &> \lim_{\delta\to\infty} CS^{SS}(p_{rl}^u) - \lim_{\delta\to\infty} CS^{BS}(p_b^*)\\ &= \frac{(1-c)^2(c(c(81c(31c+76)+52988)+25512)+12033)}{800(c^2-2c+3)(81(c-2)c+881)} > 0,\end{aligned}$$

which is what we desired to show.

□

EC.4. Omitted Figures

In this section, we include all figures referenced in the main text. First, in Fig. EC.3 we depict a swipe-based dating app. In swipe apps, users do not search directly on these platforms. Instead, they progress through a platform-generated sequence of candidate profiles. For each candidate, the user must either swipe left (to reject) or swipe right (to indicate interest). If a user swipes right on a candidate who has also swiped right on them, the two form a match. Note that in this system the platform exerts considerable control over whom a user sees. By varying a candidate's position in the sequence, the platform can increase or decrease the likelihood that the candidate is viewed.

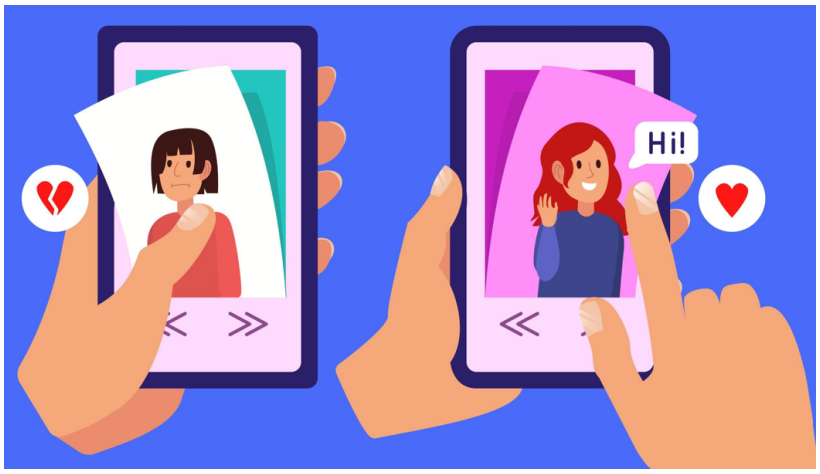


Figure EC.3 **Swipe apps.** Depicted is the basic functionality of a swipe-based dating app, where users are shown a platform-curated sequence of potential matches and move through this sequence by swiping left to reject or right to express interest.

One way users can increase their visibility to desirable candidates is by purchasing a rose. Roses boost a user's position in a candidate's queue of potential matches. In Fig. EC.4, we illustrate this mechanism by showing how a hypothetical user, Tyler, is moved from the bottom of the sequence of potential matches to the very top after sending a rose. This boost substantially increases Tyler's probability of being seen (essentially making it 100%) and therefore increases his likelihood of matching.

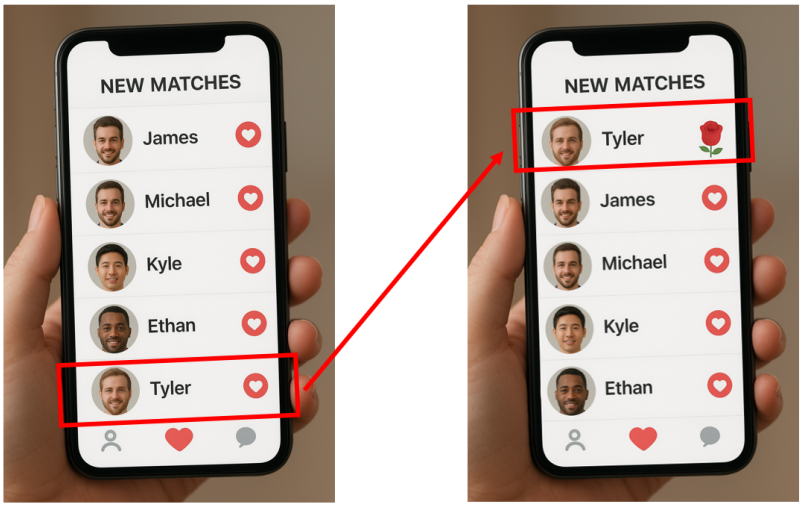


Figure EC.4 **Roses impact on user visibility.** Depicted are two candidate queue which visualize how sending a rose can elevate a user from the bottom of the sequence to the top, thereby increasing the probability that their profile is viewed.