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The Secret to Finding a Match: A Field Experiment on Choice Capacity Design in an Online Dating Platform

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Abstract. Online matching platforms require new approaches to market design because firms can now control many aspects of the search and interaction process through various IT-enabled features. Although *choice capacity*—the number of candidates a user can view and select—is a key design feature of online matching platforms, its effect on engagement and matching outcomes remains unclear. We examine the effect of different choice capacities on the number of choices and matches made on a platform by conducting a randomized field experiment in collaboration with an online dating platform. Specifically, we (1) select users who are of a similar age and live in the same geographical location, (2) design four treatment groups with different choice capacities in which users can only interact with other users in the same group, and (3) randomly assign the users to the treatment groups. We find that providing more choice capacity to male and female users has different effects on choice behaviors and matching outcomes. Although increasing the choice capacity of male users yields the highest engagement, increasing the choice capacity of female users is the most effective method to increase matching outcomes. We posit and empirically demonstrate four mechanisms underlying the effectiveness of different choice capacity designs. Furthermore, we generalize our findings to other online matching platforms and discuss how choice capacity can be designed to increase engagement and matching outcomes.

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Keywords: online matching platform design • choice capacity • online dating • field experiment

1. Introduction

The growth of the technology and infrastructure that facilitate human interconnectivity has enabled firms to build matching platforms on the internet with a variety of contexts: dating (e.g., match.com), ride sharing (e.g., Uber), accommodation (e.g., Airbnb), shopping (e.g., Amazon), and education (e.g., Udemy). Online matching platforms, often called two-sided markets, attract and connect users with common interests (e.g., males and females, drivers and riders, sellers and buyers) through a platform intermediary. One of the major challenges for online matching platforms compared with one-sided markets (e.g., online merchants) is that the matching process involves two parties that evaluate the value and decide whether to choose and accept the match. Interference from the platform on one side affects not only the users on that side, but also the users on the other side (Adachi 2003, Parker and Van Alstyne 2005). Thus, it is crucial for platforms to design the market by considering the interactions among users on the same- and cross-side networks (Li and Netessine 2020).

One of the key market design features of online matching platforms is choice capacity: the number of candidates (i.e., users on the other side) that a user can view and select. A high choice capacity represents a platform allowing users to select a large number of candidates from a large pool, thus providing an environment in which users can make many choices. On the other hand, a low choice capacity means restricting users' selection to a small number of candidates from a small pool, providing an environment in which users can make only a few choices. As making a choice (i.e., selecting a candidate to further investigate their fitness for a match) is the first step in the matching process, designing choice capacity is an important decision for online matching platforms.

However, little is known about the potential of different choice capacities and the underlying mechanisms of their effects on a platform. An investigation into online matching platforms in practice also reveals significant heterogeneity in their choice capacity designs. For example, although the majority of online dating platforms provide users with a high choice capacity (e.g., Match.com), others offer a low choice capacity (e.g., eHarmony.com) (see Piskorski et al. 2009 for details). Extant studies also recognize the importance of choice capacity in developing more efficient market design (Halaburda et al. 2018, Kanoria and Saban 2021). However, most of these studies rely on analytical approaches to show the effect of choice capacity on users' welfare, and they lack empirical evidence of and practical guidance for how to design choice capacity to increase engagement and matching outcomes. In this paper, we address this gap by empirically examining the effects of different choice capacities through a randomized field experiment and exploring the mechanisms of those effects.

We posit four mechanisms of how choice capacity affects engagement and matching outcomes on platforms based on how users select candidates under different choice capacities. First, choice capacity affects *how many* candidates users select, which might affect the overall engagement on the platform. Increasing the choice capacity of one side increases the choices made by users on that side, as the users can explore more options and select more candidates. However, that increased choice capacity might decrease the number of choices made by users on the other side as those users might select fewer candidates when they are selected more often by users with an increased choice capacity. Therefore, it is not clear whether increasing choice capacity always leads to more overall choices (i.e., engagement) on the platform. We call these competing effects the *positive same-side effect* and *negative cross-side effect*, respectively.

In addition, choice capacity also influences *whom* users select, which might ultimately affect the number of matches on the platform. When users have a high choice capacity, they might perceive a greater chance to get more matches and respond by becoming more selective (i.e., select more attractive candidates), which could decrease the conversion rate. Alternatively, users might anticipate that an increased choice capacity increases competition and respond by becoming less selective (i.e., select less attractive candidates), which could increase the conversion rate. Following Halaburda et al. (2018), we name these two distinct effects the *choice effect* and the *competition effect*, respectively. If users become less selective as their choice capacity increases, the number of matches (matching outcomes) further increases along with the increase in choices. However, if users become more selective, the conversion rate might decrease, which might counterbalance the increase in choices and reduce the number of matches. Therefore, matching outcomes might depend not only on the number of choices made but also on how those choices are made (Bruch et al. 2016). Overall, we argue that choice capacity affects engagement and matching outcomes through both of these competing effects. The objective of this study is to examine the trade-off between providing high and low choice capacity and to provide practical guidance on how to design choice capacity in a matching platform to increase engagement and matching outcomes.

Online dating platforms, the context of our study, offer an interesting opportunity to explore these four mechanisms. First, most online dating platforms allow both sides to select a potential partner, but a match only occurs when both parties agree (Kanoria and Saban 2021). This allows us to examine how users change their behavior once they are selected by users on the other side and to empirically investigate the horse race between the positive same-side effect and negative cross-side effect on a matching platform. Second, online dating platforms have two distinct groups, male and female, that might be motivated differently by the choice and competition effects because of differences in their risk perception and social position (Gustafsod 1998, Fisman et al. 2006, Croson and Gneezy 2009). Therefore, our context also offers an opportunity to identify the choice and competition effects and explore their influence on matching outcomes.

These four possible countervailing mechanisms reflect the immensely complex human behavior that manifests in matching platforms; therefore, it is difficult to study causal behavioral changes without a clear identification strategy with the microlevel data. We address our questions by conducting a randomized field experiment in collaboration with one of the largest online dating platforms in South Korea. For the experiment, we randomly assign 6,327 customers to four test groups with different choice capacities: (1) a *control* group (C), which serves as a baseline; (2) a *femaleChoice* group (T1), for which we increase the choice capacity of female users only; (3) a *maleChoice* group (T2), for which we increase the choice capacity of male users only; and (4) a *bothChoice* group (T3), for which we increase the choice capacity of both male and female users. To examine the *total effect* derived from the same- and cross-side effects on the platform, we create an isolated network for each treatment group. In addition, we randomly vary the order of the profiles shown to each user in each group to ensure that the order of the pool does not drive the results.

The results of our experiment show that increasing the choice capacity of male and female users affects the number of choices and matches differently. First, we find that increasing the choice capacity of male users (T2) leads to the highest number of choices (engagement) on the platform. This result is counterintuitive because conventional wisdom suggests that increasing the choice capacity of both male and female users (T3) should yield a larger number of choices than increasing the choice capacity of only male users (T2). Our subgroup analysis based on gender indicates that this happens because male users in the bothChoice group (T3) made significantly fewer choices compared with male users in the maleChoice group (T2). As the difference between the maleChoice group (T2) and the bothChoice group (T3) lay in the choice capacity of female users, the results imply that increasing female users' choice capacity significantly decreases the number of choices made by male users. Thus, in the bothChoice group (T3), increasing the choice capacity of female users results in an overall negative effect by decreasing the male users' choices (i.e., negative cross-side effect) by a greater magnitude than the increase in the female users' choices (i.e., positive same-side effect).

Second, we find that the femaleChoice group (T1) provides the highest number of matches (matching outcomes). This finding is also counterintuitive because increasing female users' choice capacity (T1) derives a larger number of matches than both the maleChoice group (T2), which features the highest number of choices, and the bothChoice group (T3), which provides the highest choice capacity. Our mechanism-level analysis demonstrates that this happens because male and female users behave differently as their choice capacity increases. Specifically, we find that, when users have a higher choice capacity, male users tend to select candidates who are more attractive (i.e., become more selective), whereas female users tend to select candidates who are less attractive (i.e., become less selective). This implies that, when provided with a high choice capacity, male users are mainly motivated by the choice effect, whereas female users are mainly influenced by the competition effect. Based on our results, we generalize our findings to other online matching platforms and discuss how these platforms can design choice capacity to increase engagement and matching outcomes.

Our study makes several theoretical and practical contributions. First, our study enriches the literature on online matching market design (Pizzato et al. 2010, Horton 2017, Halaburda et al. 2018, Basu et al. 2019, Shi and Zhang 2019, Li and Netessine 2020) by identifying the causal effects of choice capacity. Although designing a matching market to increase market performance is of interest to both academics and practitioners, identifying the causal effects of key design elements poses a methodological challenge because of the difficulty of controlling for network externalities and the resulting endogeneity in choice capacity (Aral and Walker 2011). By conducting a randomized field experiment, we not only investigate the effect of choice capacity, but also explore the mechanisms through which choice capacity affects engagement and matching outcomes. Thus, we make a methodological contribution to the literature by providing an experimental design that clearly identifies the causal effect of different design elements in an online matching platform.

In addition to the theoretical and methodological contributions, our study also provides solid managerial implications for increasing online platforms' engagement and matching outcomes. Based on the results of our experiments, we offer guidelines on how online platforms can design matching markets and suggest choice capacity should be designed differently based on the relative size of the network (i.e., balanced or imbalanced) and whether each side is motivated more strongly by the choice or competition effect.

The remainder of this paper is structured as follows. Section 2 provides a review of the related literature, and Section 3 explains the theoretical background of the underlying mechanisms. Section 4 describes the institutional details and our experimental design. Section 5 presents our empirical strategy and the results of our analysis. Section 6 provides guidelines for designing choice capacity to increase market performance. Finally, Section 7 concludes the paper with the managerial implications of our work and directions for future research.

2. Literature Review

2.1. Online Matching Platform Design

An online matching platform is a marketplace that establishes matches between users on two sides (Parker and Van Alstyne 2005, Chen et al. 2020). Online matching platforms require high user engagement because users on each side have heterogeneous idiosyncratic preferences that cannot be easily discovered by the platform and because matching involves decisions by both sides (Pizzato et al. 2010, Kanoria and Saban

2021, Shi and Zhang 2019). Therefore, online matching platforms must pay considerable attention to market design for efficiency, welfare, and performance (Bapna et al. 2016).

Studies explore various approaches to efficient market design by (1) facilitating IT-enabled technologies (e.g., recommendation systems, matching algorithms, and ranking systems), (2) introducing new features (e.g., authentication, signaling, and standardization), and (3) restricting interactions or reducing the information available to users. One stream of the literature on online matching platform design focuses on the design of recommendation systems and matching algorithms to reduce search frictions (Horton 2017, Basu et al. 2019, Lee et al. 2020, Li and Netessine 2020). As the online matching market involves a bilateral decision rather than a single-side purchasing decision as in the product market, studies suggest that recommendation systems and matching algorithms should consider the preference of users on both sides (Pizzato et al. 2010, Shi and Zhang 2019). Horton (2017) provides empirical evidence that algorithmic recommendations of workers to employers for the purpose of recruiting substantially increase the hiring rate. In the context of Airbnb, Fradkin et al. (2018) show that tracking listing availability reduces hosts' rejection rate and incorporating host preferences into rankings increases the matching rate.

Another stream of the literature focuses on adding new features and elements to market design for market efficiency (Cullen and Farronato 2020, Basu et al. 2019, Horton 2019). Horton (2019) suggests that a signaling feature that labels users with a higher capacity increases market surplus by increasing the number of matches and decreasing costs. Basu et al. (2019) investigate how pricing strategies and the design of authentication services better serve a broad range of customers in online matching platforms. Using data from the labor market platform TaskRabbit, Cullen and Farronato (2020) show that even standardizing tasks that freelancers perform can improve market efficiency and market growth.

Finally, several studies focus on how online matching platforms can improve market efficiency and welfare by restricting interactions or reducing the amount of information disclosed to users (Allon et al. 2012, Halaburda et al. 2018, Kanoria and Saban 2021, Arnosti et al. 2021). For instance, in the context of the labor market, Arnosti et al. (2021) show that decreased application costs result in fiercer competition and lower employer welfare. Thus, they suggest that a layer of friction in the application process (e.g., charging a larger fee and restricting the number of applications) enhances overall user welfare. Kanoria and Saban (2021) show that hiding information about the quality of potential partners improves the overall welfare. Relevant to our study, Halaburda et al. (2018) show how online dating platforms with limited choice capacity successfully compete against those with unlimited choice capacity. The authors show that users with fewer outside options prefer a platform with limited choice capacity because they are mainly influenced by the competition effect.

Our study is closely related to this last stream of the literature. Although Halaburda et al. (2018) investigate how users switch between platforms under the assumption that all users on a platform are affected by either the choice or competition effect, we empirically show how users' behaviors change under different choice capacities and how these changes in behavior translate into market performance. Additionally, most of the studies in this stream of the literature provide theoretical evidence based on the analytical modeling approach, whereas only a handful of studies present empirical evidence. For instance, Li and Netessine (2020) show some empirical evidence that an increase in market thickness leads to lower matching rates because of increased search friction in the rental marketplace. However, their analysis relies on observational data. Our approach differs from theirs in that our experimental design allows us to directly manipulate the market thickness of each side through choice capacity and to identify the underlying mechanisms by investigating how users strategically change their behavior in response to the behavior changes of users on the other side. To the best of our knowledge, this is the first empirical study to show how choice capacity in an online matching platform affects same- and cross-side users' engagement and matching outcomes by conducting a randomized field experiment.

2.2. Online Dating

This study also contributes to the nascent but growing literature on online dating markets. Recent studies of information systems examine the effects of new features and new channel adoption in the online dating context. For example, Bapna et al. (2016) examine how viewing a potential partner's profile anonymously works as a weak signal of preference. Shi and Viswanathan (2018) investigate the adoption and effectiveness of phone verification as a trustworthiness signal in online dating outcomes. Belo and Li (2018) examine the effectiveness of referral programs in the growth of online dating platforms. Burtch and Ramaprasad (2016) investigate network effects in the online dating context by examining the impact of seeding new users in a platform. Jung et al. (2019) show the changes in engagement and matching outcomes following the launch of an online dating service's mobile application.

Although previous studies focus on how IT-enabled new features and channels affect users on online dating platforms, little is known about how to design choice capacity in online dating platforms from cross- and same-side network perspectives using microlevel data. We strengthen the literature on online dating by showing how each gender strategically changes its choice behaviors under different choice capacities and how this affects engagement and matching outcomes.

The vast majority of the literature on online dating in the economics and psychology fields examines matching and sorting patterns (Hitsch et al. 2010a, Bruch and Newman 2018) and gender differences (Lin and Lundquist 2013, Ong and Wang 2015) when selecting potential partners. Although a few studies examine the effect of choice on online dating (Fisman et al. 2006, Lenton and Stewart 2008), these studies mostly focus on the selection of a potential partner from a choice set from the single-side perspective. Given the distinctive market characteristics of a two-sided online dating platform, this study is among the first to examine choice capacity and sequential choice behavior from a two-sided market perspective.

3. Mechanisms

One of the main objectives of this study is to explore the mechanisms by which choice capacity affects market performance. Specifically, we propose four mechanisms that offer countervailing predictions on how choice capacity affects the number of choices and matches in an online matching platform. In this section, we discuss the theoretical background of each mechanism and its implications for market design.

3.1. Positive Same-Side Effects and Negative Cross-Side Effects

In terms of the number of choices, conventional wisdom suggests that users select more candidates as their choice capacity increases. This aligns with the theoretical literature on matching platforms that assumes positive cross-side effects (e.g., Diamond 1982): the increased size of one side increases the overall utility of the other side. When a platform provides high choice capacity, users value having more abundant options and try to gather more information about the various candidates on the platform (Katz and Shapiro 1985), especially in the online context, in which search costs are low (Bakos 1997). This leads users to search for more candidates and increase the number of choices they make. We refer to this effect as the positive same-side effect.

However, providing a higher choice capacity to one side might not always increase the total number of choices on the platform as it could decrease the number of choices made by users on the other side. Previous studies show that users establish relationships based on mutual interests, and therefore, users are more attracted to potential partners who are interested in them (Fiore and Donath 2004, Shtatfeld and Barak 2009). This implies that, if a user on the other side receives more choices, the user tends to commit to suitors who show interest and ultimately makes fewer choices (Argyle and Henderson 1985). We refer to this effect as the negative cross-side effect.

Efforts to evaluate these two competing effects are limited because of the difficulty in tracing and measuring users' choice behavior under different choice capacities. We fill this gap and advance the literature by conducting a randomized field experiment with different choice capacities and collecting granular user-level data.

3.2. Choice Effects and Competition Effects

There are competing accounts regarding how users perceive high choice capacity in matching platforms. Users might expect a higher choice capacity to increase their chance of getting a match. This aligns with prior research demonstrating that users' expectations of getting a match increase as the assortment size increases (Diehl and Poynor 2010). Alternatively, users might anticipate that a higher choice capacity decreases their chance of getting a match. If users expect other same-side users to select more candidates based on the higher choice capacity, they might expect their choices to be less reciprocated because of increased competition. This effect is similar to a finding by Cachon et al. (2008), who show that, although customers' low search cost may put pressure on retailers to lower their prices, low search costs can lead to higher prices because of greater exposure to other customers. That is, each retailer gains more access to a broader pool of potential customers, which increases the competition on the customer side. Overall, increasing choice capacity enhances the perception of both the benefit (i.e., higher chances to get a match) and the cost (i.e., greater likelihood of rejection) of getting a match. We call these two competing effects the choice effect and the competition effect, respectively (Halaburda et al. 2018).

Identifying whether users emphasize the benefit or cost in response to an increase in choice capacity affects whom users select, thereby providing important implications for market design. If users place more weight on the benefit (i.e., motivated by the choice effect), they select more attractive candidates as their choice capacity increases. This aggressive behavior might adversely result in lower conversion rates and fewer matches. However, if users focus more on the cost (i.e., motivated by the competition effect), they select less attractive candidates as their choice capacity increases. This conservative behavior might counterintuitively lead to higher conversion rates and more matches (Beshears et al. 2008).

It is possible that users on each side are motivated primarily by either the choice or the competition effect, and the forces that determine which effect is more prominent differs depending on the context. In the online dating context, gender differences in risk perception and social position might influence which primary motivation is more salient for male and female users (Gustafsod 1998, Fisman et al. 2006, Croson and Gneezy 2009).[1] Several studies in economics and psychology document a consistent pattern regarding gender differences in risk perception: women express greater concern about risks. One plausible explanation is that males are more likely to perceive a risky situation as a challenge to overcome, whereas females interpret risky situations as threats to avoid (Arch 1993).

In addition, male users have a lower cost of rejection than female users because of differing social norms for men and women in setting up dates (Scharlott and Christ 1995, Fisman et al. 2006, Bapna et al. 2016). For example, Vorauer and Ratner (1996) show that women are more hesitant about making the first move as they have a greater fear of rejection than men. In this regard, we expect that male users are mainly motivated by the choice effect and become more selective, whereas female users are mainly motivated by the competition effect and become less selective as they have higher choice capacity.[2]

Although previous studies show how people select potential partners (Todd et al. 2007, Hitsch et al. 2010b), no study yet investigates how users strategically change their selections as their choice capacity changes. We contribute to the literature by causally examining the role of choice capacity on users' selectivity and matching outcomes.

4. Institutional Setting and Experimental Design

We conduct a randomized field experiment in collaboration with one of the largest online dating platforms in South Korea, which has more than 100,000 daily active users. The platform does not provide a search feature for users to access available candidates on the platform.[3] Instead, the platform provides users with a limited number of candidate profiles each day from which they can select. These candidates are determined by the platform's matching algorithm.

Specifically, when a user joins the platform,[4] the user is shown a pair of two simplified heterosexual user profiles side by side. This process is repeated until the number of pairs shown reaches a certain threshold.[5] When a focal user[6] receives a pair of two candidates, the focal user can decide whether to select one or see the next pair of candidates.[7] If the focal user selects one of the two candidates, the platform sends a notification to the selected candidate that the candidate's profile was selected by the focal user. Next, both the focal user and the selected candidate can decide to view the other's detailed profile.[8] If one of them clicks and views the other's detailed profile, that person can further decide whether to send an invitation to initiate a chat. If the user decides to send an invitation, the other user receives a notification about the chat invitation and decides whether to accept the invitation. Selecting a simplified profile in the first stage is free, but a user must spend in-app currency to view a detailed profile or send a chat invitation.[9] A visual representation of how two users can enter a chat is presented in Figure A1 of Online Appendix A. Overall, the platform provides an ideal context in which to study our research questions because the platform can manipulate the choice capacity of each user.

As previously mentioned, we expect choice capacity to affect female and male users' behavior differently. Therefore, we design four test groups with different choice capacities: (1) a *control* group (C), which serves as the baseline; (2) a *femaleChoice* group (T1), for which we increase the choice capacity of female users only; (3) a *maleChoice* group (T2), for which we increase the choice capacity of male users only; and (4) a *bothChoice* group (T3), for which we increase the choice capacity of both male and female users. The descriptions of the choice capacities of each treatment group are listed in Table 1. It is important to note that we use the choice capacity typically used in the platform as the baseline (i.e., female users receive 30 pairs of profiles per day and male users receive 10 pairs of profiles per day) because this choice capacity allows female and male users to make approximately equal numbers of choices on average. This is consistent with the literature that shows that male users view and select three times more profiles than female users on an online dating platform (Finkel et al. 2012, Kreager et al. 2014).

To examine both the direct effects of choice capacity on user behavior and the indirect effects that occur through same- and cross-side effects, we carefully design the experiment as follows. First, we isolate each treatment group by only allowing interactions between users in the same group. Specifically, we design the matching algorithm on the platform so that, during the experiment, the focal users only receive sets of profiles of heterosexual users from within the same treatment group, and the profiles of the focal users are only shown to heterosexual users within the same group. This design approach allows us to prevent any spillover effects from other groups and to identify the same- and cross-side effects of choice capacity in a group. This approach has not been widely used in network experiments because implementing comprehensive control over each individual user's network environment is extremely challenging (Aral and Walker 2011). However, we overcome this challenge by

Table 1. Summary of Experimental Groups and Choice Capacities

Test group	Female users	Male users
Control Group (C)	Receive 30 pairs of male users' profiles per day	Receive 10 pairs of female users' profiles per day
femaleChoice group (T1)	Receive 60 pairs of male users' profiles per day	Receive 10 pairs of female users' profiles per day
maleChoice group (T2)	Receive 30 pairs of male users' profiles per day	Receive 20 pairs of female users' profiles per day
bothChoice group (T3)	Receive 60 pairs of male users' profiles per day	Receive 20 pairs of female users' profiles per day

creating isolated networks. Second, we randomly vary the order of pairs shown to each user in the experiment. As the order of pairs might affect users' choice behaviors differently, it is crucial to ensure that the order of pairs is orthogonal to each user's preference. This allows us to clearly examine the effect of choice capacity by disentangling the order effect from the effect of choice capacity. Third, to ensure that users only see relevant profiles during the experiment, we carefully select subjects who are in a similar age range and live in the same geographical area. Finally, we ensure that a user does not see the same heterosexual user profile more than once during the experiment. Overall, our experimental design gives us strong control over the randomized field experiment by using clear manipulation and reducing the issue of potential interference.[10]

Based on our experimental design, we selected 6,327 users aged 24–34, who had lived in the same metropolitan area and used the platform at least once in the seven days prior to our experiment. Next, we randomly assigned them to one of the four groups and conducted the experiment for three days in January 2019. We collected data at the individual user level, including online activities (i.e., choice, view profile, send invitation, and chat), demographic information (i.e., age, gender, occupancy, tenure, body type, and mate preference), and monetary activities (i.e., in-app currency purchase and acquisition and use of in-app currency) from three weeks prior to the experiment to the end of the experiment.[11]

Before reporting the results of the analysis, we compare the differences in user characteristics between the four groups to ensure randomization. Table 2 demonstrates that our sample is well balanced across all of the covariates, supporting the validity of our randomization procedure.[12]

5. Empirical Analysis and Results

For market performance measures, we operationalize two outcome variables: (1) the number of choices a focal user made and (2) the number of chats in which a focal user participated. The first outcome characterizes user engagement, and the second outcome characterizes matching outcomes.[13] To identify the effect of different choice capacities on user engagement and matching outcomes, we run regression models at the user level. Specifically, we relate the outcome variables to the control variables and the dummy variables, which indicate each treatment group, to directly compare the key outcomes between groups while controlling for other factors. We use the ordinary least squares method in Equation (1). Our main estimation equation for user i is

$$\lambda_i = \alpha + \beta_1 \times femaleChoice_i + \beta_2 \times maleChoice_i + \beta_3 \times bothChoice_i + Controls + \varepsilon_i, \tag{1}$$

where λ_i is the outcome variable of interest; *femaleChoice* indicates whether a user is assigned to the femaleChoice group (one) or not (zero); *maleChoice* indicates whether a user is assigned to the maleChoice group (one) or not (zero); and *bothChoice* indicates whether a user is assigned to the bothChoice group (one) or not (zero). *Controls* indicates the control variables, which include individual specific characteristics (i.e., attractiveness, body type, height, age, tenure, religion, smoking, drinking habit, and verifications), potential partner preferences (i.e., religion, body type, smoking, and drinking habit), and past engagement behaviors (i.e., spending, choice, view profile, and chat). As our dependent variables are nonnegative integer values, we also estimate our model using several count models (Poisson, negative binomial, and zero-inflated Poisson models) to ensure that the results are robust and consistent with the results of our main analysis (see Table A3 in Online Appendix A for details).

5.1. The Effects of Choice Capacity on Engagement

We report the effect of each treatment (i.e., increasing the choice capacity of female, male, and both female and male users) on user engagement (number of choices) in Table 3. First, we find that the number of choices increased significantly in both the femaleChoice group (T1) and the maleChoice group (T2) compared with the control group: by 8% and 116%, respectively (Table 3, column (1)).[14] We also find that the number of choices increased significantly, by 102%, in the bothChoice group (T3) compared with the control group. Among the three treatment groups, the maleChoice group (T2) generated significantly more choices: 100% more than the femaleChoice group (T1) and 7% more than the bothChoice group (T3).

These results are counterintuitive because it is reasonable to expect that increasing the choice capacity of both male and female users (T3) would generate

Table 2. Randomization Check

Test group	Sample size	Gender		Age		Tenure		Attractiveness[23]	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
C (Control)	1,578	0.0792	0.2702	29.24	3.1275	162.09	220.21	2.1375	0.8343
T1 (femaleChoice)	1,575	0.0787	0.2694	29.15	3.1874	163.25	226.41	2.1379	0.8838
T2 (maleChoice)	1,601	0.0887	0.2844	29.20	3.1944	164.67	219.92	2.1669	0.8708
T3 (bothChoice)	1,573	0.0871	0.2821	29.27	3.1173	168.16	223.08	2.1653	0.8588
p-value for joint test		0.6420		0.7306		0.8824		0.6314	

Test group	Past spending		Past choice		Past view profile		Past send invite		Past chat	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
C (Control)	29.54	95.59	26.38	30.71	6.1768	33.34	0.4911	2.1466	0.2947	1.3090
T1 (femaleChoice)	30.16	94.09	25.01	26.80	5.9098	29.75	0.4438	2.1599	0.2654	1.2294
T2 (maleChoice)	29.97	111.35	24.40	25.53	6.2580	34.78	0.4166	2.3245	0.2829	1.1529
T3 (bothChoice)	25.02	82.77	26.16	28.29	5.4075	30.79	0.4094	2.2367	0.2384	1.0705
p-value for joint test	0.3856		0.1430		0.8800		0.7245		0.5750	

more choices than increasing the choice capacity of male users only (T2). To further understand the mechanisms underlying the results, we conduct the same analysis by gender and present the results in columns (2) and (3) of Table 3. When we compare the difference between the maleChoice group (T2) and the bothChoice group (T3) (i.e., increasing female users' choice capacity while keeping male users' choice capacity the same), we observe both positive same- and negative cross-side effects. First, we find that female users made more choices as their choice capacity increased, confirming the positive same-side effect (β_2 = 1.4763, β_3 = 5.4546, p-value = 0.1143, column (2)). Second, we find that male users made fewer choices as the choice capacity of female users increased, substantiating the negative cross-side effect (β_2 = 11.4924, β_3 = 9.8318, p-value < 0.0001, column (3)). Thus, the results indicate that, in the bothChoice group (T3), increasing the choice capacity of female users significantly decreased the number of choices made by male users, and this reduction outweighs the increase in choices by female users.

We also observe the two opposite effects when comparing the femaleChoice group (T1) with the bothChoice group (T3) (i.e., increasing male users' choice capacity while keeping female users' choice capacity the same). Although increasing the choice capacity of male users increased the number of choices they made (i.e., positive same-side effect) (β_1 = 0.1827, β_3 = 9.8318, p-value < 0.0001, column (3)), it also decreased the number of choices that females made (i.e., negative cross-side effect) (β_1 = 7.7962, β_3 = 5.4546, p-value = 0.3723, column (2)). However, in this case, the decrease in choices made by females is smaller than the increase in choices made by males, partially because of the smaller percentage of female users on the platform. Overall, our results show that increasing choice capacity exerts both positive same- and negative cross-side effects, and the negative cross-side effect dominates the positive same-side effect when the platform increases the choice capacity of the short side (i.e., the female side in our context). We extend our findings to implications for market design and provide practical guidance in Section 6.

5.2. The Effects of Choice Capacity on Matching Outcomes

We report the effect of each treatment on matching outcomes (number of chats) in Table 4. We find that the femaleChoice group (T1) yielded the most matching outcomes compared with the other treatment groups. The number of chats in the femaleChoice group (T1) was significantly higher than that in not only the control group (C), by 113%, but also the maleChoice group (T2), which had the highest engagement, by 57% (Table 4, column (1)). Moreover, the

Table 3. The Effects of Choice Capacity on Engagement

Dependent variable	Number of choices		
	(1)	(2)	(3)
Sample	Total	Female	Male
β_1 (femaleChoice)	0.7335* (0.4046)	7.7962*** (2.6814)	0.1827 (0.0120)
β_2 (maleChoice)	10.5597*** (0.4032)	1.4763 (2.6546)	11.4924*** (0.3743)
β_3 (bothChoice)	9.2866*** (0.4043)	5.4546** (2.6205)	9.8318*** (0.3754)
p-value ($\beta_2 - \beta_1$)	<0.0001	0.0173	<0.0001
p-value ($\beta_3 - \beta_1$)	<0.0001	0.3723	<0.0001
p-value ($\beta_3 - \beta_2$)	0.0016	0.1143	<0.0001
Control group mean	9.0963	9.0805	9.2800
Controls	Yes	Yes	Yes
Observations	6,327	528	5,799
R^2	0.4815	0.5405	0.5442

Note. Robust standard errors are in parentheses.
*Significant at 10%; **significant at 5%; ***significant at 1%.

number of chats in the femaleChoice group (T1) was higher than that in the bothChoice group (T3), which had the highest choice capacity by 25%. However, this difference is not statistically significant.

To better understand the mechanisms underlying these results, we further investigate whether choice capacity affects users' selections. As mentioned, we expect male and female users to behave differently when presented with greater choice capacity. Specifically, female users, who place more emphasis on the costs of high choice capacity (i.e., greater likelihood of rejection), are mainly motivated by the competition effect and select less attractive partners. However, male users, who place more emphasis on the benefits of high choice capacity (i.e., higher chances to get a match), are mainly influenced by the choice effect and select more attractive partners.

To investigate which type of candidate partners each gender selects, following the approach of Bruch and Newman (2018), we construct a measure, *attractiveness_gap*, that is the difference in the percentile attractiveness ranks of two users who make and receive a choice. For example, if the least attractive woman selects the most attractive man, then the *attractiveness_gap* is +1 (i.e., 1 − 0); if the most attractive woman selects the least attractive man, then the *attractiveness_gap* is −1 (i.e., 0 − 1). Therefore, a higher *attractiveness_gap* value implies that a user selects a candidate who is more attractive than the user. We investigate the differences in attractiveness and conversion rates based on the choices made under different choice capacities and present the results in Figure 1.[15]

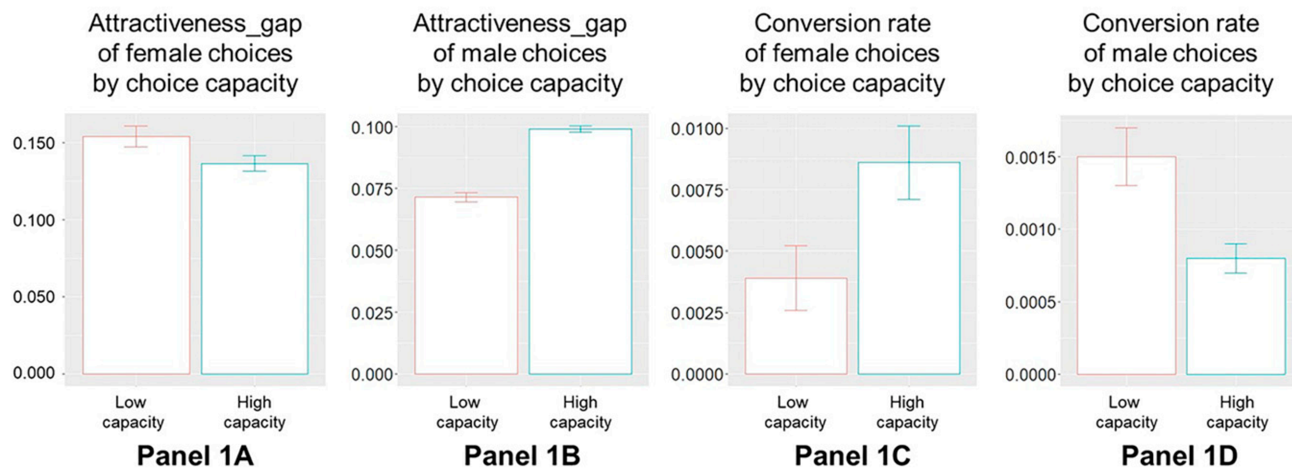
The results depicted in Figure 1 confirm our theoretical predictions regarding behavioral changes and their subsequent matching outcomes. First, we find significantly different patterns in the attractiveness gap between genders when users are provided with a high versus low choice capacity. The *attractiveness_gap* of the choices made by females with a low choice capacity was significantly higher than that of the choices made by females with a high choice capacity (Panel 1A). These results indicate that, when female users have a high choice capacity, they tend to select less attractive candidates. For male users, however, we find the opposite pattern (Panel 1B). That is, the *attractiveness_gap* of the choices made by males with a high choice capacity was significantly higher than that of the choices made by males with a low choice capacity. This implies that male users become more selective and select more attractive candidates when they have a high choice capacity. These findings show that the choice effect is dominant for male users, whereas the competition effect is dominant for female users. Second, we find a similar pattern for the conversion rate, as shown in Panels 1C and 1D. Specifically, we find that the conversion rate of female choices was significantly higher under a high choice capacity than under a low choice capacity. For male choices, the conversion rate was significantly higher under a high choice capacity than under a low choice capacity.

Table 4. The Effects of Choice Capacity on Matching Outcomes

Dependent variable	Number of chats
β_1 (femaleChoice)	0.0287*** (0.0096)
β_2 (maleChoice)	0.0091 (0.0095)
β_3 (bothChoice)	0.0178* (0.0096)
p-value ($\beta_2 - \beta_1$)	0.0398
p-value ($\beta_3 - \beta_1$)	0.2543
p-value ($\beta_3 - \beta_2$)	0.3616
Control group mean	0.0253
Controls	Yes
Observations	6,327
R^2	0.2459

Note. Robust standard errors are in parentheses.
*Significant at 10%; **significant at 5%; ***significant at 1%.

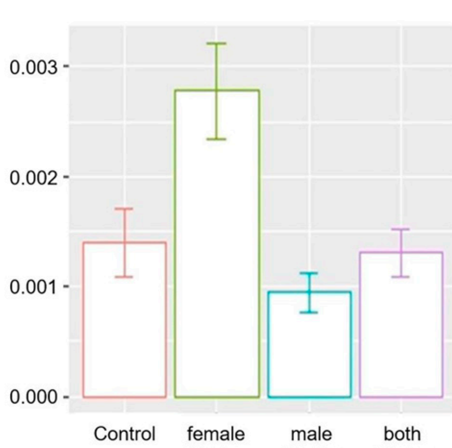
Figure 1. (Color online) Different Choice Behavior by Gender Depending on Choice Capacity



We further compute the conversion rate of the choices made in each treatment group and report the results in Figure 2.[16] As shown in Figure 2, we find that the conversion rate of choices in the femaleChoice group (T1) was significantly higher than that in the control group (C) by 99%; in the maleChoice group (T2) by 194%; and in the bothChoice group (T3) by 112%. The results show that, although the number of choices made in the femaleChoice group (T1) was not the highest, the choices made in that group more often resulted in a chat. Therefore, the femaleChoice group (T1) yielded the highest number of matching outcomes.

In summary, the results of our experiment demonstrate that increasing the choice capacity affects engagement and matching outcomes for male and female users differently. Specifically, we find that increasing the choice capacity of male users (long side) is the best way to increase engagement. However, in terms of matching outcomes, our results show that increasing the choice capacity of female users, who are mainly motivated by the competition effect, leads to the highest number of matching outcomes. Interestingly, increasing the choice capacity of both male and female users results in neither the highest engagement nor the highest matching outcomes. Practically, our results suggest that firms should carefully design choice capacity as there is a fundamental trade-off between increasing the choice capacity of male and female users. In addition, increasing the choice capacity of both sides could lead to suboptimal outcomes. Our results also suggest that the number of choices and matches derived from choice capacity might change based on the gender composition of the platform.[17] We further discuss detailed market design strategies in Section 6.

Figure 2. (Color online) Conversion Rate of Choices by Group



5.3. Additional Analysis of Other Dating Funnels and Revenue

Having identified the effect of choice capacity on user engagement and matching outcomes, we examine the effect of choice capacity on other intermediate stages along the dating funnel[18] as well as its effect on revenue. Specifically, we operationalize three additional dependent variables as follows: (1) the number of profiles a focal user viewed (i.e., view profile), (2) the number of invitations a focal user sent (i.e., send invite), and (3) the total in-app currency each user spent (i.e., revenue).

Next, we repeat the same analysis as in Equation (1). The results are presented in Table 5. Table 5 indicates that the maleChoice group (T2) was the only treatment

Table 5. The Effects of Choice Capacity on the Matching Funnel

	View profile	Send invite	Revenue
Dependent variable	(1)	(2)	(3)
β_1 (femaleChoice)	0.1186 (0.2076)	0.0065 (0.0148)	0.1613 (0.2212)
β_2 (maleChoice)	0.3793* (0.2069)	0.0281* (0.0148)	0.4835** (0.2204)
β_3 (bothChoice)	0.2026 (0.2075)	0.0227 (0.0148)	0.2592 (0.2210)
p-value ($\beta_2 - \beta_1$)	0.2078	0.1443	0.1438
p-value ($\beta_3 - \beta_1$)	0.6861	0.2752	0.6582
p-value ($\beta_3 - \beta_2$)	0.3928	0.7153	0.3086
Control group mean	0.6521	0.0652	3.7972
Controls	Yes	Yes	Yes
Observations	6,327	6,327	6,327
R^2	0.2383	0.5019	0.2791

Note. Robust standard errors are in parentheses.
*Significant at 10%; **significant at 5%; ***significant at 1%.

group in which all three outcomes of interest increased significantly compared with the control group. Note that the intermediate outcome variables (the number of views and number of invitations) are closely related to user engagement. Also, the platform charges users for these activities (views and invitations) by fully monetizing user engagement at each point along the matching funnel. Thus, the strategy to maximize revenue is consistent with the strategy to maximize user engagement, such as the number of choices, number of views, and number of invitations (increase the choice capacity of the long side only). However, the strategy to maximize revenue might differ depending on a platform's pricing scheme. If a platform relies heavily on matching for revenue (users pay only after they are matched), then the strategy to maximize revenue could align with the strategy to maximize matching outcomes (increase the choice capacity of the competition-effect dominant side only). Taken together, we confirm that the results for other engagement metrics are similar to those for the number of choices, and the best way to boost engagement and revenue is to increase the choice capacity of male users.

6. Guidance on Market Design

In this section, we discuss the optimal market design strategy and provide practical guidelines for how platforms can leverage choice capacity to improve engagement and matching outcomes.[19] First, in terms of engagement, our results demonstrate that increasing choice capacity generates the negative cross-side effect, and this effect can dominate the positive same-side effect when the platform increases the choice capacity of only the short side in an imbalanced market. That is, when the choice capacity of the short side increases, the negative cross-side effect (i.e., decrease on the long side) might outweigh the positive same-side effect (i.e., increase on the short side) and result in an overall negative impact. Therefore, for an imbalanced market, platforms should increase the choice capacity of the long side only. However, for a balanced market, platforms should increase the choice capacity of both sides to maximize engagement.

Second, in terms of matching outcomes, the optimal choice capacity depends on whether each side is mainly motivated by the choice or the competition effect. If one side is mainly driven by the choice effect, platforms should restrict the choice capacity on that side to yield a better outcome. However, if users on one side are mainly driven by the competition effect, increasing the choice capacity on that side increases matching outcomes. We present these guidelines in Table 6.

We believe that our guidelines can be applied beyond the context of online dating to other online matching platforms. For example, consider an online labor market (e.g., Indeed.com, CareerBuilder.com) that centralizes the interaction between job applicants and employers and controls the job openings and applications that each side can view. According to our guidelines, the optimal choice capacity to maximize

Table 6. Optimal Market Design Guidelines

Objective	Market characteristic	Market design guideline
Increase engagement	Balanced market	Increase choice capacity of both sides
	Imbalanced market	Increase choice capacity of the long side only
Increase matching outcomes	Users on one side are mainly motivated by the choice effect	Restrict choice capacity of that side
	Users on one side are mainly motivated by the competition effect	Increase choice capacity of that side

engagement[20] differs based on whether the market is balanced or imbalanced. For platforms in which the number of applicants is sufficiently larger than the number of employers, increasing only the choice capacity of applicants (i.e., the long side) leads to the highest level of engagement. However, when there are comparable numbers of applicants and employers in the market, increasing the choice capacity of both applicants and employers yields the highest level of engagement.

If the focus of a platform is on maximizing matching outcomes (i.e., signing contracts), the platform should design its choice capacity based on whether applicants and employers are mainly motivated by the choice or competition effect. As mentioned, the forces that determine which effect serves as each side's primary motivation might differ according to context. Market concentration is a main driving force in online labor markets (Azar et al. 2020). If a labor market is highly concentrated (e.g., a few firms dominate hiring), employers are mainly motivated by the choice effect (i.e., seek to find ideal candidates). However, in a market with low concentration, employers are mainly motivated by the competition effect (i.e., tend to hire any available candidate). This is supported by previous studies that show that employers defer posting job openings until they find ideal candidates when the market is highly concentrated, whereas employers offer higher wages to indifferent candidates when market concentration is low. For instance, Azar et al. (2020) provide empirical evidence of different labor market concentrations among different U.S. commuting zones by examining the job openings posted by each company. They show that, although the majority of local markets are highly concentrated, areas around large cities tend to have lower levels of market concentration, which explains the city wage premium (Yankow 2006, Baum-Snow and Pavan 2012). These empirical findings suggest that, although employers are driven by the choice effect in most labor markets, they can also be driven by the competition effect in a less concentrated market. In terms of applicants, Azar et al. (2020) show that the average concentration of job applicants is normally higher than the average concentration of job openings, implying that applicants might be mostly motivated by the choice effect rather than the competition effect.

After identifying the effects by which applicants and employers are mainly motivated, the platform could design the optimal market by increasing the choice capacity of the side that is mainly motivated by the competition effect. For instance, if job applicants are mainly driven by the choice effect, whereas employers are motivated by the competition effect, then restricting the choice capacity of applicants and increasing the choice capacity of employers yields the highest matching outcomes.

Our guidelines can also be applied to another online matching platform context, 3D printing platforms. A 3D printing platform, such as MakeXYZ and 3DEXPERIENCE, connects designers in need of 3D printing and suppliers who offer 3D printing services for a fee (Rayna et al. 2015). In the 3D printing marketplace, the platform facilitates interaction between designers and suppliers and controls the requests and offers that each side can view (Pahwa and Starly 2020). To increase user engagement, such as browsing, writing reviews, and providing ratings, our guideline suggests that the platform increases the choice capacity of the long side when the marketplace is imbalanced. For example, when the number of designers is sufficiently larger than the number of suppliers, increasing the choice capacity of the designer side is the best way to increase engagement. When the numbers of designers and suppliers are similar (i.e., a balanced market), increasing the choice capacity of both sides could yield the highest engagement.

To increase matching outcomes on a 3D printing platform, it is crucial to identify the driving forces that determine the dominant effect on each side. A major driving force on 3D printing platforms is design specifications. For designers, if the design specifications are highly customized and use expensive composite materials, such as carbon fiber, titanium, and precious metals, they are mainly motivated by the choice effect. In this case, designers tend to find the 3D printing suppliers with the best quality who support various printing materials, printing types, and intricate designs or suppliers who specialize in the design specifications requested. However, designers are driven by the competition effect if the design specification follows standard 3D printing guidelines and uses common materials, such as polylactic acid and acrylonitrile butadiene styrene (Redwood et al. 2017). Designers driven by the competition effect tend to select 3D printing suppliers that are available nearby at low cost. From the 3D printing suppliers' perspective, the choice effect dominates when they can support a wide range of design specifications in terms of printing types, materials, and sizes, or when they specialize in specific printing types or materials. Therefore, these 3D printing suppliers might choose suitable and profitable clients by assessing their design specifications. However, 3D printing suppliers are driven by the competition effect if they only support common and widely used printing types, such as fused deposition modeling and stereolithography apparatus materials (Redwood et al. 2017). In this case, 3D printing suppliers support limited design specifications and tend to select readily acceptable requests from designers because many other 3D printing suppliers provide similar services.

After identifying the effect that mainly drives each side, the platform should increase the choice capacity of the side or sides that are driven by the competition effect. For example, if designers are dominated by the choice effect, but 3D printing suppliers are driven by the competition effect, the optimal design to increase matching outcomes would be to restrict the choice capacity of designers and increase the choice capacity of suppliers. In this case, the platform could increase the choice capacity of suppliers by providing a wide range of design requests with various sorting options or fine-tuned recommendations. Therefore, a 3D printing platform should differentiate the choice capacity for optimal matching based on whether the choice or competition effect determines each side's demand.

7. Conclusion

Concurrent with advances in information technology and the en masse relocation of various activities from off-line to online channels, online matching platforms have become a disruptive force in many industries. As firms can now provide various IT-enabled features to improve matching, these matching markets require new approaches to market design. Although choice capacity is a key design feature that critically affects market performance, its effect on matching platforms is woefully understudied. In this paper, we present a novel randomized experiment that allows us to examine this question and make a causal inference. Specifically, we design four treatment groups with different choice capacities, in which users can only interact with other users in the same group. Then, we select users who are in a similar age range and live in the same geographical location and randomly assign users to each treatment group. Our design enables us to address the various challenges of the empirical analyses conducted in previous studies. First, by creating an isolated network for each group, we eliminate potential interference between test groups, which is one of the biggest challenges in matching market experiments. Second, by randomizing the order of the profiles shown to each user in the experiment, we disentangle the effect of choice capacity from the order effect that might alter the results.

Our results provide empirical evidence of the four proposed mechanisms through which choice capacity affects user engagement and matching outcomes. First, we find competing effects of increasing choice capacity on user engagement. Specifically, the results demonstrate that increasing the choice capacity of one side increases the engagement of that side (i.e., positive same-side effect) but decreases the engagement of the other side (i.e., negative cross-side effect). Second, we find different effects of increasing choice capacity on users' choice behavior (i.e., whom users select) and matching outcomes. More specifically, presented with high choice capacity, female users become less selective (i.e., motivated by the competition effect), whereas male users become more selective (i.e., motivated by the choice effect).

Finally, we provide practical guidance for the market design of online matching platforms. We suggest that providing a high choice capacity to the long side (e.g., male users in an online dating platform) only is the best strategy to increase user engagement when the market is imbalanced because the positive same-side effect is larger than the negative cross-side effect only when the choice capacity of the long side is increased. In addition, we suggest that providing a higher choice capacity to the competition-dominant side (e.g., female users in an online dating platform) is the most effective way to increase matching outcomes because the choices made by less selective users result in a higher conversion rate.

Our findings have both theoretical and practical implications. First, our results suggest that firms should be aware of the fundamental trade-offs of increasing choice capacity when designing their markets. Specifically, increasing the choice capacity of both sides guarantees neither the highest engagement nor the most matching outcomes. Indeed, the findings of our experiment explain why recent dating applications, such as Bumble,[21] have designed their choice capacity to allow only female users to make the first move. In addition, our study presents that a one-size-fits-all choice capacity design that simultaneously results in the highest engagement and most matching outcomes might not exist. Rather, the optimal choice capacity is a function of the market characteristics and motivations that manifest on each side of a platform. Therefore, firms should strategically design choice capacity for optimal engagement and matching outcomes.

Second, although we focus on the context of online dating platforms, we believe that our work is generalizable beyond that context to other matching platforms. This generalizability stems from our identification of the underlying mechanisms that lead to changes in users' behavior as the platform increases users' choice capacity. Specifically, we see the mechanisms of the negative cross-side effect and competition effect happening across the board, ranging from our context of dating to college admissions and, even more broadly, to the labor market. Although the bilateral matching environment allows users to obtain matches that better account for their idiosyncratic preferences (Kanoria and Saban 2021), the literature in this area is sparse. Our paper spearheads much needed research in this underserved stream of the literature.

This paper has limitations that could be addressed in future research. First, our study was conducted in South Korea. As dating norms vary among countries (Hatfield and Rapson 1996), future research could apply our experimental design to other countries to test whether the findings are consistent. Second, when we vary the choice capacity in our experiment, we manipulate both the size of the candidate pool and the number of possible choices (i.e., users can either choose a small number of candidates from a small pool or choose a large number of candidates from a large pool). However, each choice capacity element might have different effects on user behavior. For example, increasing the size of the candidate pool but maintaining the number of possible choices could have a different effect than holding the size of the candidate pool constant and increasing the number of possible choices. We expect future work to study each choice capacity element separately. Finally, our study was conducted on an online dating platform with an imbalanced gender ratio. Although this is a common phenomenon,[22] future research could extend our findings and investigate how choice capacity might affect user engagement and matching outcomes differently in balanced environments.

In conclusion, understanding the effects of choice capacity on engagement and matching outcomes is a crucial step in developing optimal design strategies for matching markets. Through a randomized field experiment, this study enriches the literature on matching market design, two-sided network effects, and online dating by providing a framework of choice capacity and insights into the underlying mechanisms.

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Endnotes

[1] We further discuss the examples of forces under different contexts (e.g., labor market and 3D Printing) in Section 6.

[2] This aligns with prior studies that suggest that both men and women are strategic in their mate selection (Walster et al. 1966) and might become either more or less selective as they have more choice opportunities (Shtatfeld and Barak 2009).

[3] In the context of online dating, in which users have heterogeneous idiosyncratic preferences, it is challenging for platforms to provide suitable candidates without a search function. Nevertheless, more and more platforms are trying to understand users' preferences based on demographics, surveys, and previous behaviors so that they can identify suitable candidates and create a market with greater efficiency. Other examples of dating platforms that are using similar approaches are OkCupid and eHarmony.com.

[4] A user can sign up by setting up the user's own online profile. All new users go through a screening process before they are approved to join. As the platform does not allow direct contact between users before they initiate a chat, a user cannot reveal the user's phone number or email address in their profile. This information is deleted automatically during the screening process.

[5] Although the platform sends the same number of pairs of profiles to each user by gender, because of gender differences in behavior and an imbalanced gender ratio, the platform sends more pairs to female users (e.g., 30 pairs per day) than to male users (e.g., 10 pairs per day). Also, a simplified profile includes one photo and information regarding age range, location, and occupation.

[6] The term "focal user" denotes a user of interest in a network (e.g., the subject of this study) and is used to explain the relationship between users in social network studies.

[7] Even after a user chooses one of the two profiles, the user can go back and go through the rest of the pairs of profiles available that day (e.g., if the platform sends a user 10 pairs of profiles in one day, the user can choose up to 10 profiles in that day).

[8] A detailed profile includes additional photos and more detailed information regarding hobby, body type, smoking and drinking habits, religion, self-introduction, etc.

[9] In-app currency can be purchased or acquired through various actions on the platform (e.g., rating others' profiles). Sending an invitation costs about four times more than viewing a detailed profile.

[10] We conduct several analyses to ensure that the manipulation was performed as intended and present the results in Online Appendix B.

[11] See Table A1 in Online Appendix A for details on the measurement of the variables.

[12] Engagement-related variables (e.g., past spending, past choice) are computed based on user activities during the seven days prior to the experiment.

[13] We focus on the number of choices because this is the first step to initiating an interpersonal relationship, and it is closely related to overall engagement and the profits of online dating platforms (Sprecher 2009, Heino et al. 2010, Hitsch et al. 2010b, Oestreicher-Singer and Zalmanson 2013). In terms of matching outcomes, following Bapna et al. (2016), we define a match as two users successfully initiating an online communication. Although users typically exit a dating platform after achieving a successful match, successfully matched users spread positive word of mouth after the fact. This draws in more new users and ultimately benefits the platform (Jung et al. 2019). Therefore, the number of choices and matches are important measures for both platforms and users.

[14] We compute the percentage change based on the increased number of choices for each treatment group in comparison with the control group (i.e., (control group average + treatment coefficient)/control group average). We provide the summary statistics of the results in Table A2 in Online Appendix.

[15] The summary statistics of the results are outlined in Table A4 of Online Appendix A.

[16] The summary statistics of the results are outlined in Table A5 of Online Appendix.

[17] We use counterfactual analysis to understand whether and how the optimal design of choice capacity to maximize market performance changes as the gender proportion changes, and the results are shown in Online Appendix C.

[18] Similar to the term "sales funnel" or "conversion funnel," "dating funnel" refers to the sequence of stages a user goes through that results in a date. In our context, these stages include making a choice, viewing a profile, sending an invitation, and chatting.

[19] To further support our argument on how the optimal choice capacity changes based on the gender ratio, we model individual users' choice behavior and conversions of choices at the microlevel using random utility models and conduct a counterfactual analysis. The detailed specifications and results are provided in Online Appendix C.

[20] In the online labor market, the number of searches or messages a user makes can be regarded as engagement.

[21] Bumble is the second most popular dating app in the United States with more than five million monthly users as of September 2019 (Statista 2019).

[22] A recent report by Ogury reveals a massive gender imbalance among dating app users in various countries (https://ogury.com/perspectives/research-and-insights/dating-app-study-how-lovers-match-in-a-mobile-first-world/). For example, the average proportion of male users on online dating platforms is 85% and 91% in the United Kingdom and Italy, respectively.

[23] Users on the platform can anonymously evaluate other users' attractiveness on a scale from one (least attractive) to five (most attractive).

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